İSTANBUL TECHNICAL UNIVERSITY ★ INSTITUTE OF SCIENCE AND TECHNOLOGY

RISK MANAGEMENT TECHNIQUES IN AN ENERGY COMPANY

Ph.D. Thesis by
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Department : **Management Engineering**

Programme : **Management Engineering**

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

ENERJİ FİRMASINDA RİSK YÖNETİMİ TEKNİKLERİNİN UYGULANMASI

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FOREWORD

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This thesis is dedicated to my grandmother and my mother...

July 2011 Hülya Keskintaş Sarı

Management Engineering

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ABBREVIATIONS

ARCH : Autoregressive Conditional Heteroscedasticity
ARMA : Autoregressive-Moving Average
CAPM : Capital Asset Pricing Model
CFTC : Commodity Futures Trading Commission
COSO : the Committee of Sponsoring Organizations
EEX : European Energy Exchange
ERM : Enterprise Risk Management
GARCH : Generalized Autoregressive Conditional Heteroskedasticity
HFLS : High-Frequency, Low Severity
ICE : IntercontinentalExchange
IPE : International Petroleum Exchange
LFHS : Low-Frequency, High Severity
LTCM : Long-Term Capital Management
NYMEX : New York Merchantile Exchange
OECD : The Organization for Economic Co-operation and Development
OPEC : The Organization of the Petroleum Exporting Countries
OTC : Over the Counter
P/L : Profit Loss
PC : Principal Component
PCA : Principal Component Analysis
RAROC : Risk Adjusted Return
TOCAM : Tokyo Commodity Exchange
VaR : Value at Risk
WTI : West Texas Intermediate

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RISK MANAGEMENT TECHNIQUES IN AN ENERGY COMPANY

SUMMARY

This study investigates the contribution of market risk management process into an energy company. The energy firms are exposed to price risk due to having commodity stocks and volatile oil prices. To be able to mitigate price risk, the quantification of price risk, choosing of hedging instruments and the hedging methodology determining the hedge level are crucial issues in decision making. The performance of Value at Risk models at measuring risk for the portfolio consisting of physical stocks; gasoil, gasoline, fuel oil, jet, crude oil and hedging instruments gasoil and crude oil futures contracts were assessed regarding minimum VaR hedge ratio of the portfolio called as optimal hedge ratio of the portfolio. All VaR analysis in three approach, historical simulation, parametric (variance-covariance) method and monte carlo has been executed at two quantiles for 30 different days: 0.95 and 0.99. In parametric VaR analysis, the volatility of portfolio calculation requires the variance covariance matrix of portfolio. Principal component analysis (PCA) has been used to decrease the number of elements modeled by multivariate generalized autoregressive conditional heteroskedasticity (GARCH) analysis in var-cov matrix. The hedge efficiencies of three approach have been compared with each other and the best fitting model result will be challenged with non-hedged portfolio P/L. Close results of three different methodology regarding hedge efficiencies and hedge ratio strengthens the necessity of risk management for energy company.

ENERGY FİRMASINDA RİSK YÖNETİMİ TEKNİKLERİNİN UYGULANMASI

ÖZET

Bu çalışmada piyasa risk yönetimi tekniklerinin enerji firmasında uygulanmasının firmaya katkıları araştırılmıştır. Enerji firması sahip olduğu stoklar ve ürün fiyatlarındaki dalgalanmalar yüzünden fiyat riskine maruz kalmaktadır. Fiyat riski ile mücadelede, fiyat riskinin ölçülebilmesi, hedge enstrümanının seçimi ve hedge seviyesinin belirlenmesinde etkili olan hedge yöntemi karar vermede en etkili konulardır. Portföy fiziksel stoklardan ve hedge enstrümanlarından oluşmaktadır. Fiziksel ürün portföyünde motorin, benzin, fuel oil, jet ve ham petrol, hedge portföyünde ise ham petrol ve motorin futures kontratları bulunmaktadır. Çalışmada portföyün riskliği Riske Maruz Değer yaklaşımlarıyla ölçülmüş ve portföyün minumum RMD değerine ulaştığı nokta optimum hedge oranı olarak belirlenmiştir. Tarihsel simulasyon, parametrik metot ve monte carlo olmak üzere üç yöntemle yürütülen RMD analizleri 30 farklı gün için %95 ve %99 güven aralıkları için yapılmıştır. Parametrik yöntemle yapılan RM analizinde, portföyün varyans hesaplaması varyans kovaryans matriksini de gerektirmektedir. Genelleştirilmiş otoregresif koşullu değişen varyans (GARCH) modeliyle yöntemi kullanılarak modellenecek olan varyans-kovaryans matriksinin eleman sayısını azaltmak amacıyla Ana bileşenler analizi (PCA) kullanılmıştır. Üç yöntemin hedge verimlilikleri birbirleriyle kıyaslanmış ve en uygun model kullanılarak yapılan hedge sonrası rakamları hedge yapılmayan portföyün K/Z analiz ile kıyaslanmıştır. Üç modelinde gerek hedge verimliliği gerekse minumum hedge oranı konusunda birbirine yakın sonuçlar vermiş olması, seçilen hedge enstrümanlarının ve yöntemin uygunluğu ve risk yönetiminin enerji piyasasında gerekliğini kuvvetlendirir niteliktedir.

1. RISK MANAGEMENT

1.1 The Risk Management Need

“Risk management” is the process of achieving the desired balance of risk and return through a particular trading strategy. The risk/return framework includes the full business process of selecting, communicating, valuing and achieving the balance in the firm’s portfolio of assets. The term “risk management” can be decomposed into its components as “risk” and “management”. Risk suggests the defining and quantifying the unknown. How the risk/return balance should change as a function of movement in the total portfolio due to changes in risk factors such as prices, volatility, interest rates or/and time. Quantification needs mathematical and statistical background in addition to qualified data. On the other hand, management embeds more comprehensive content related with business process. Management requires communication, evaluation and achievement of the company’s desired balance of risk and return. It depends on business skills different from risk side. It is less quantified. For risk management to be effective, both technical competency and good management are required (Crouhy and Mark, 2001).

Due to globalization and economic crises, the competition between financial or nonfinancial corporations has increased drastically. To survive, corporations have to possess professional staffs and experienced senior management. Moreover, the ability of managing business risks determines the survival of company. Why are risks and risk management so important? Weren’t they in the past? Let’s start with risk definition before these questions. The global definition of risk is that the unexpected variability or volatility of returns and thus includes both potential worse-than-expected as well as better-than-expected returns. Risks are future issues that can be avoided or mitigated, rather than present problems. Managing of risks means not only mitigation or avoidance of risk but also monitoring the accepted risk creating competitive advantages. Let’s look at the cases leading to development in risk management.

1.2 The Contributory Factors Leading To Risk Measurement Revolution

1.2.1 Volatile environment

The increased volatility of financial markets since 1970s enhanced the need for risk management. The high level of instability in the economic environment within firms is one of the important factors affecting rapid risk management development. A volatile environment exposes firms to greater financial risk and therefore provides an incentive for firms to find new and better ways of managing the risk. Volatility in stock market, exchange rate, interest rate and commodity market value increases uncertainty in the economic environment.

Big financial crisis leading increases in the volatility are;

- Flexible and volatile exchange rates due to the fixed exchange rate system broke down in 1971
- High inflation and fluctuations in interest rates due to the oil-price shocks in 1973 causing the 1973–1974 stock market crash
- Secondary banking crisis of 1973–1975 – United Kingdom
- 1980s – Latin American debt crisis – beginning in Mexico in 1982 with the Mexican Weekend
- Bank stock crisis (Israel 1983)
- The devaluation of US stocks by 23 %, which is USD 1 trillion on Black Monday which is October 19 in 1987.
- 1989–91 – United States Savings & Loan crisis
- 1990 – Japanese asset price bubble collapsed
- early 1990s – Scandinavian banking crisis: Swedish banking crisis, Finnish banking crisis of 1990s
- 1992–93 – Black Wednesday – speculative attacks on currencies in the European Exchange Rate Mechanism, Monetary unification in Europe
- Financial crises in Japan 1992 due to Japanese stock price bubble, which led the Nikkei index from 39,000 to 17,000 3 years later.

- Six consecutive interest increase by the Federal Reserve Bank due to the bond debacle of 1994
- 1994–95 – 1994 economic crisis in Mexico – speculative attack and default on Mexican debt
- 1997–98 – 1997 Asian Financial Crisis – devaluations and banking crises across Asia
- The Russian default in August 1998, resulting in huge losses of Long Term Capital Management.
- 2001 – Bursting of dot-com bubble – speculations concerning internet companies crashed
- 2007–10 – Financial crisis, followed by the late 2000s recession and the 2010 European sovereign debt crisis

All above mentioned events have increased the need of risk management in especially financial markets and energy companies due to the increased gain/loss potential.

1.2.2 Growth in trading activity

Huge increase in trading activity since late 1960s is another factor contributing to the risk management development. Traded shares in exchange markets have increased enormously. There have been massive increases in the range of instruments traded over the past three or four decades and trading volumes in these new instruments have also grown rapidly. New instruments have been developed in offshore markets and more recently in the newly emerging markets of Eastern Europe, China, Latin America, and Russia. New instruments have also arisen for assets that were previously illiquid, such as consumer loans, commercial and industrial bank loans, mortgages, mortgage-based securities and similar assets and these markets have grown very considerably since the early 1980s.

Until 1972 the only derivatives traded were certain commodity futures and various forwards and over the counter (OTC) options. The Chicago Mercantile Exchange started trading foreign currency futures contracts in 1972 and in 1973 the Chicago Board Option Exchange started trading equity call options. Interest rate futures were introduced in 1975 and the following years, swaps and exotics (swaptions, futures on interest rate swaps) took off and followed by catastrophe, credit, and electricity and weather derivatives in the 1990s.

1.2.3 Advances in information technology

Improvements in IT have made possible huge increases in both computational power and the speed with which calculation can be carried out. This led to new techniques able to used (e.g. such as computer intensive simulation techniques used frequently in risk management analysis) to enable the risk managers to tackle more difficult calculation problems. Besides speed, the risk managers found the chance to use sophisticated algorithms programmed into computers to carry out real time calculations that were not possible before.

1.3 Case Studies

1.3.1 Metallgesellschaft

In December of 1993, Metallgesellschaft cashed out its positions and reported losses of 1.5 billion USD.

Metallgesellschaft Refining and Marketing is an American subsidiary of Metallgesellschaft, an international trading, engineering, and chemicals conglomerate. In 1991, the Company implemented a marketing strategy designed to insulate customers from price volatility in petroleum markets for a fee.

Firm strategy is that it offered customers contract to buy fixed amounts of heating oil and gasoline at a fixed price over a 5 or 10 year period. The fixed price was set at a USD 3 to 5 per barrel premium over the average futures price of contracts expiring over the next 12 months. Metallgesellschaft would pay the customer half of the difference between the futures price and contract price if the spot price rose above the fixed price in the contract. By these customer contacts, Metallgesellschaft had a short position in long-term forward contracts. To hedge these positions, Metallgesellschaft could use near-term futures due to illiquidity of long-term futures contracts. Metallgesellschaft used stack-and-roll[1] hedging strategy.

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[1] In stack-and-roll strategy, the firm buys a bundle of futures contract with the same expiry date, known as a stack and the liquidates the stack and buys another stack of contracts with longer expirations, known as roll.

In the second half of 1993, the average trading volume was 15 to 30 million barrels per day. Metallgesellschaft had open position in unleaded gasoline contracts were 55 mb/d.

The fundamental problem in this case was a cash flow problem that caused the company's inability to ride out the hedge. Besides cash flow problem, here the maturity mismatch also is influential in these losses.

In 1993, oil prices dropped from 21 USD per barrel to 14 USD per barrel and this fall caused losses on Metallgesellschaft's long position, which were realized immediately as the futures contracts were marked to market. The offsetting gains on their customer contacts would not be realized for years to come, which caused short-term cash outflows and led to funding liquidity risk.

Moreover, basis risk which is the difference between futures price and spot price also played very important role. Before 1993, the petroleum futures markets exhibited normal backwardation[2] in which futures prices are less than spot prices. In a backwardation, stack-and-roll strategy hedge benefits from selling a short term contract at a relatively high price with narrow basis risk because it narrows as contracts approach expiry. However, in 1993, the market inverted to contango and basis risk increased. The shift from normal backwardation to contango increased the cost of rolling hedge and accelerated the cash flow problems.

1.3.2 Sumitomo

In May of 1996, Sumitomo reported 2.6 billion USD and 150 million USD fine from the Commodity Futures Trading Commission (CFCT) due to speculative actions in copper market.

Yasuo Hamanaka is a trader for Sumitomo and attempted to corner the copper market by buying large quantities of physical copper and taking a long position in futures. A lack of operational and risk controls permitted him to continue taking positions. The copper market was relatively small and this led Hamanaka to control and corner the market. When the futures contracts approached delivery, the party

[2] Backwardation is a downward sloping forward curve. A backwardation starts when the difference between the forward price and the spot price is less than the cost of carry, or when there can be no delivery arbitrage because the asset is not currently available for purchase. Contango means the expected spot price at maturity is lower than the forward price. Futures contract price includes compensation for the risk transferred from the asset holder.

with short position would find little physical copper for its delivery and would be forced to either pay a huge amount of premium or could not close its short position by offsetting long futures position. Humanaka's aim is to get profit from either way, the increase in copper price and/or copper futures price. Humanaka's risk here is falling price of copper.

What were the preventing factors of this loss? High degree of supervision and constrained power could prevent this risk occurrence. No one in Sumitomo Company impeded Hamanaka until CFCT noticed the manipulation. In December 1995, CFCT investigated the physical and futures buying and realized that the Company did not need the amount of copper bought by Hamanaka. The Institution saw the price increase by manipulation of market. In May of 1996, Hamanaka took new position by the same strategy but in this time, other traders would took the same position and this led to price fall in copper so Sumitomo lost 2.6 billion USD different from fine by CFCT. Hamanaka was jailed.

1.3.3 Long-Term Capital Management

The total losses were found to be USD 4.6 billion. Long-Term Capital Management (LTCM) was founded as a hedge fund in 1994. The managers of Company managed the fund very successfully. Thus the hedge fund got large amounts of returns. Their returns were 43% in 1995 and 41% in 1996. In 1998, it had USD 125 billion of assets on USD 4.7 billion of equity capital, yielding leverage of 28 to 1.

LTCM's investment strategies based on relative value, credit spreads and equity volatility. What was the risk of the Fund? The most important is its model risk. Its model assumed that historical relationship were useful predictors of futures relationships. In August of 1998, Russia unexpectedly defaulted o its debt and led Russia interest rate increasing to 200% and decreasing the value of ruble. This shock increases the correlation between different instruments that hedge funds invest. After Russia defaults, credits spreads, risk premiums, liquidity premiums and volatility in the world increased so the risk has increased. LTCM partly could adjust the possibility by using correlations that were greater than historical correlations but the model could not capture the spike in correlations caused by economic shocks.

Traditional VaR model underestimates risk in the tail of distribution due to ignorance of correlation (trigger effect) of low frequency/high frequency events.

LTCM diversified its portfolio to different assets, and used various strategies but its all trading strategies were based on declining of risk premiums and market volatility. But this unexpected economic shock created blank in its strategy and so market risk arose.

Due to the ability of LTCM's market maker, its liquidity problems led falling prices. Like Metallgesellschaft and Sumitomo, LTCM had also liquidity risk.

1.3.4 Barings

Nick Leeson lost USD 1.3 billion. Unlike Metallgesellschaft and LTCM, the collapse of Barings Bank was caused by operational risk and the lack of segregation of duties. Nick Leeson was a trader in Barings. He took speculative derivative positions to compensate his trading losses, USD 296 million that he could hide fraudulently and reported USD 46 million to senior management. Due to inadequate control systems, the losses were not reported, no one noticed. In addition to his previous losses, Leeson created huge losses on both the short and the double-long futures position because in Jan of 1995, an earthquake hit Kobe and Japan and this event risk caused market risk arouse. How could Barings' bankruptcy be prevented?

All traders in the Bank should have been required to meet London International Financial Futures Exchanges' expectations. The segregation of duties should have been used so trading and settlement functions must have been done separately by different business units. Moreover, accurate information system was important. In addition to these, senior management oversight was very important.

If the segregation of duty in the Bank and the internal control function were settled efficiently, the losses could be stopped at the beginning so the losses were not so huge.

1.3.5 MotherRock

The high volatility and its leveraged positions led to a loss of around USD 230 million in June and July, 2006.

MotherRock was a hedge fund founded in December 2004, one of the biggest traders of Natural Gas derivatives in New York. It invested in natural gas futures to get profit from price differences based on contracts. Besides futures, it also traded options based on gases. In the beginning of year, the fund's was USD 400 million and on June of 2006, it had USD 280 million in assets.

MotherRock had lost up to USD 300 Million. It was small compared to Amaranth's case but this case was also influential for Amaranth due to its being buyer of many positions of MotherRock. It closed in August 2006, the prime cause of which was attributed to the high volatility in natural gas valuations in the commodities market.

1.3.6 Amaranth

It lost approximately USD 5.8 billions, which was two-thirds of its value due to liquidity problems.

Amaranth was a multi-strategy hedge fund founded in 2000. The founders had professional experiences in convertible bonds. Later, the fund concentrated on merger arbitrage, long-short equity, leverage loans, blank-check and energy trading. As of June in 2006, energy trades accounted for half of the fund's capital and generated 75 % of its profits (Till, 2008).

Due to the nature of gas futures market, the volatility of prices has been very high. Difficulty in transportation, unusual shape of futures curve were important features leading to huge losses. From 1990 to 2005, the average return for short-term contracts had been positive. Moreover, there had been positive profits in most years from a spread strategy in long position. In September of 2006, return pattern was reversed and the average return for short-term contract was negative and they had lower returns (larger losses) than longer-term contacts. Winter months had larger losses than non-winter months. The amount of losses raises the important question that how the firm could get huge amount of position under regulatory authorities. Due to Amaranth's trading strategy based on long-short strategy, futures market authorities could not notice its huge position. In September, the expected nominal return was USD 1 billion and VaR of about USD 3.2 billion. The actual loss was greater than VaR due to liquidity risk.

1.3.7 Enron

Enron reports its first quarterly loss in four years, $618 million US, and a reduction in shareholder equity of over $1 billion.

Enron was an American energy company, which was one of the world's leading electricity, natural gas, communications and pulp and paper companies, with claimed revenues of nearly $101 billion in 2000. Before its bankruptcy in late 2001, the number of employee reached to approximately 22,000.

At the end of 2001, it was revealed that the reported financial condition was sustained substantially by institutionalized, systematic, and creatively planned accounting fraud, known as the "Enron scandal".

Enron case is different from the other cases regarding the causing factors. No single factor was the reason of Enron's crashing down to earth from its sky-high success. The failure of risk management and internal control led this bankruptcy. Combination of five key internal controls which are management oversight control culture, information and communication, risk assessment, controls and monitoring led to huge losses of Enron.

Although the risk management system was established and there were sophisticated tools to measure derivatives' risk, the management continued to get stock-option profits not to decelerate the firm's expansion. So the public report was seen very well and the profits were very high and this brought the value addition in stock prices. In addition to this, the competition between Enron's staff prohibited them to declare the real situation to senior management because they risked getting fired. In spite of access to risk management systems, Enron expanded its trading portfolios with new areas previously no professional experience the traders had. From its core business of natural gas, oil and power trading, it ended up in markets such as sea freight, pulp and paper, aluminum and weather derivatives but Enron had less experienced players in those fields and this led to big losses.

In addition to management failure and the lack of effective risk management system, the lack of appropriate external regulatory controls that allowed Anderson Accounting to audit and also consult Enron was the other important contributing factor for its bankruptcy. The lack of segregation of duties and the fear of losing profitable consulting compared to account fees led to increase the losses. Moreover, the lack of monitoring the data coming out increased the loss amount.

1.4 Risk Management Tools

Technological improvements and developments in financial theories affected the evolution of analytical risk management tools. Chronological evolution of analytical risk management tools are listed below.

The Evolution of Analytical Risk Management Tools (Jorion, 2000)

1938	Bond Duration
1952	Markowitz mean-variance framework
1963	Sharpe's capital asset pricing model
1966	Multiple factor models
1973	Black-Scholes option pricing model, "Greeks"
1979	Binomial option model
1983	RAROC, risk-adjusted return
1986	Limits on exposure by duration bucket
1988	Risk-weighted assets for banks, Limits on "Greeks"
1992	Stress testing
1993	Value at risk (VaR)
1994	RiskMetrics
1997	CreditMetrics, CreditRisk+
1998	Integration of credit and market risk
2000	Enterprise wide risk management

Markowitz (1952) issued a paper concerning the principles of portfolio selection which contained the foundations of modern risk analysis. Markowitz emphasized that rational investor should analyze alternative portfolios based on their mean and on the variance of their rates of return. Markowitz made two assumptions: that capital markets are perfect and the rates of return are normally distributed.

Sharpe (1964) and Lintner (1965) took the portfolio approach one step further by adding the assumption that a risk free asset exists. It was shown that if all portfolios in the market consist of riskless assets, the financial markets are in equilibrium.

Therefore, prices of risky assets are determined in such a way that they are included in the market portfolio. Then, one of the most important developments in risk management is “Capital Asset Pricing Model” (CAPM). The model was proved and tested in discrete time. Merton (1972) has shown that the CAPM can also be derived in a continuous time framework, under the assumptions that trades can be executed at any tine and the return-generating process for stock prices is smooth, with no jumps in prices.

Pricing on option is the next important improvement is risk analysis. Two papers about this subject were issued by Fischer Black and Myron Scholes and Robert Merton in 1973. Similar to previous scientists, they also assumed that perfect capital market exists and security prices are log-normally distributed (or log-returns are normally distributed). In addition to them, they also suggested that trading in all securities is continuous and the distribution of the rates of return is stationary. All these are the leading studies for risk management. In the Table 1.1, the studies on quantitative analysis are listed.

Table 1.1 : Studies in quantitative analysis.

Citation	Area	Topic
Allen, L., Boudoukh, J. and Saunders, A. (2004)	**Quantitative Analysis**	Volatility in VaR Models
Hull, J. (2003)	**Quantitative Analysis**	Estimating volatilities and correlations
Jorion, P. (2000)	**Quantitative Analysis**	Forecasting risk and correlations Monte Carlo Methods.
Kalyvas, L. and Akkizidis,I. (2006)	**Quantitative Analysis**	Extreme Value Theory and in Risk Management.
Spiegel, M.R, Schiller, J. and Srinivasan, R.A. (2000)	**Quantitative Analysis**	Basic Probability Random Variables and Probability Distributions Mathematical Expectation Special Probability Distributions Sampling Theory Estimation Theory Tests of Hypotheses and Significance Curve Fitting, Regression, and Correlation

In the Table 1.2, the studies in market risk management have been shown. In the Table 1.3, the studies in credit risk management can be founded.

Table 1.2 : Studies in market risk management.

Citation	**Area**	**Topic**
Allen, Boudoukh, and Saunders (2004)	**Market Risk Management**	Introduction to Value at Risk (VaR Putting VaR to Work
Hull (2003)	**Market Risk Management**	Hedging Strategies using Futures Determination of Forward and Futures Prices Interest Rate Futures Swaps Properties of Stock Options Trading Strategies Involving Options Binomial Trees The Black-Scholes-Merton Model The Greek Letters Volatility SmilesExotic Options
Jorion (2000)	**Market Risk Management**	VaR Methods Mapping Stress Testing
McDonald.R (2003)	**Market Risk Management**	Commodity Forwards and Futures
Saunders, A. (2005)	**Market Risk Management**	Market Risk Foreign Exchange Risk
Stulz, R. (2003)	**Market Risk Management**	A Firm-Wide Approach to Risk Management Identifying and Managing Cash Flow Exposures The Demand and Supply for Derivative Products
Bruce Tuckman, B. (2002)	**Market Risk Management**	Bond Prices, Discount Factors, and Arbitrage Bond Prices, Spot Rates, and Forward Rates Yield to Maturity Generalizations and Curve Fitting One-Factor Measures of Price Sensitivity Measures of Price Sensitivity Based on Parallel Yield Shifts Key Rate and Bucket Exposures The Science of Term Structure Models Mortgage-Backed Securities

Table 1.3 : Studies in credit risk management.

Citation	**Area**	**Topic**
Canabarro, E. and Duffie,D. (2003)	**Credit Risk Management**	Measuring and Marking Counterparty Risk
Culp, C. (2006)	**Credit Risk Management**	Securitization
Servigny, A. and Renault,O. (2004)	**Credit Risk Management**	External and Internal Ratings Default Risk: Quantitative Methodologies Loss Given Default Credit Risk Portfolio Models Credit Risk Management Strategic Capital Allocation
Dev, A., (2004)	**Credit Risk Management**	Economic Capital for Counterparty Credit Risk
Meissner, G (2005)	**Credit Risk Management**	Credit Derivatives Products Synthetic Structures Application of Credit Derivatives Risk Management with Credit Derivatives
Saunders (2005)	**Credit Risk Management**	Credit Risk: Individual Loan Risk Credit Risk: Loan Portfolio and Concentration Risk Sovereign Risk Loan Sales and Other Credit Risk Management Techniques
Stulz (2003)	**Credit Risk Management**	Credit Risks and Credit Derivatives
Sharma (1996)	**Credit Scoring**	Discriminant Analysis Logistic Regression

As mentioned as case studies, the importance of operational risk management has increased and the studies in this area in Table 1.4 are listed.

Table 1.4 : Studies in operational and integrated risk management**.**

Citation	Area	Topic
Allen, Boudoukh, and Saunders	**Operational and Integrated Risk Management**	Extending the VaR Approach to Operational Risk
Crouhy,M. , Galai,D. and Mark,R. (2001)	**Operational and Integrated Risk Management**	Capital Allocation and Performance Measurement
Culp. C. (2001)	**Operational and Integrated Risk Management**	Identifying, Measuring, and Monitoring Liquidity Risk
Davis, E. (2006)	**Operational and Integrated Risk Management**	Operational Risk Economic Capital Measurement: Mathematical Model
Renault, S	**Operational and Integrated Risk Management**	Regulation
Dowd, K.	**Operational and Integrated Risk Management**	Model Risk
Gallati, R. (2003)	**Operational and Integrated Risk Management**	Case Studies
Kalyvas and Akkizidis (2006)	**Operational and Integrated Risk Management**	Operational Risk
Kuritzkes, A., Schuermann, A and Weiner, S.M. (2003)	**Operational and Integrated Risk Management**	Capital Adequacy in Financial Conglomerates
Nocco, B.W. and Stulz,R.M. (2006)	**Operational and Integrated Risk Management**	Enterprise Risk Management: Theory and Practice
Saunders (2005)	**Operational and Integrated Risk Management**	Technology and Other Operational Risks
Stulz (2003)	**Operational and Integrated Risk Management**	Investors and Risk Management, Creating Value with Risk Management
Counterparty Risk Management Policy Group II (July 2005)	**Operational and Integrated Risk Management**	Counterparty Risk

Standards in Enterprise Risk Management area are listed in Table 1.5.

Table 1.5 : Studies in enterprise risk management.

Citation	Area	Topic
The Committee of Sponsoring Organizations c	**Enterprise Risk Management**	Enterprise Risk Management
ISO 31000 (2009)	**Enterprise Risk Management**	Enterprise Risk Management

Increased volatility in energy commodity returns strengthened the importance in energy risk management. In Table 1.6, the studies in this area are listed.

After 2000, the studies on energy risk management have been increased.

Table 1.6 : Topics in energy risk management.

Citation	Area	Topic
James, T (2008)	**Energy Risk Management**	Risk Management in Energy Markets Operational Risk and its Management Energy Futures Contracts Option Trading and Hedging Application Strategies Energy-Market Hedging Scenarios Credit Risk Management for the Energy Industry Accounting for Energy Derivatives Trades
Burger,M., Graeber,B. and Schindlmayr,G. (2007)	**Energy Risk Management**	Energy Derivatives Fundamental Market Models Value at Risk and Further Risk Measures Energy-Credit Risk
Dahl, C.A. (2004)	**Energy Risk Management**	Energy Futures and Options Markets for Managing
Errera, S. And Brown, S.L. (2002)	**Energy Risk Management**	Behavior of Commodity Futures Prices Speculation and Spread Trading Energy Options Strategies
Kaminski, V. (2004)	**Energy Risk Management**	Energy Swaps Energy Options Energy Exotic Options
Pilipovic, D. (2007)	**Energy Risk Management**	Essential Statistical Tools Spot Price Behavior The Forward Price Curve Volatilities Option Pricing for Energies Option Valuation
Beutel, P.C.(2005)	**Energy Risk Management**	Understanding Futures and Options Energy Prices
Clewlow, L.and Strickland, C. (2000)	**Energy Risk Management**	Volatility Estimation in Energy Markets Spot Price Models and Pricing Standard Instruments Energy Derivatives
Eydeland, A. And Wolyniec, K. (2003)	**Energy Risk Management**	Energy and Power Risk Management
Geman, H. (2008)	**Energy Risk Management**	Forward Curve Modelling in Commodity Markets Case Studies and Risk Management in Commodity Derivatives Trading Price Risk Management and Trading
Mauro, A. (1999)	**Energy Risk Management**	Price Risk Management - VaR
Leppard, S. (2005)	**Energy Risk Management**	Pysical Transactions and Basic Hedging Instruments
Sturm, F. (1997)	**Energy Risk Management**	Hedging and Trading Instruments
Fusaro, P.C. (1998)	**Energy Risk Management**	Hedging Strategies and Instruments for the International Energy Markets

1.5 Enterprise Wide Risk Management

In today's volatile and competitive economy, business opportunities and risks has changed drastically. Risk identification, risk assessment, monitoring the organization's business opportunities and risks are inevitable steps in risk management process. In this stage, how to implement the risk management process is fundamental.

COSO defines ERM as "*a process, affected by an entity's board of directors, management, and other personnel, applied in strategy setting and across the enterprise, designed to identify potential events that may affect the entity, and manage risk to be within its risk appetite, to provide reasonable assurance regarding the achievement of entity objectives.*

This definition reflects certain fundamental concepts. ERM is:

- *A process, ongoing and flowing through an entity*
- *Effected by people at every level of an organization*
- *Applied in strategy*
- *Applied across the company and includes taking an entity level portfolio view of risk*
- *Designed to identify potential events affecting the entity and manage risk within its risk appetite*
- *Able to provide reasonable assurance to an entity's management and board*
- *It is "a means to an end, not an end in itself" (p.4)*

ERM encompasses:

- *Aligning risk appetite and strategy: The entity's risk appetite in evaluating strategic alternatives, setting related objectives, and developing mechanisms to manage related risks.*
- *Enhancing risk response decisions: risk avoidance, reduction, sharing, and acceptance.*
- *Reducing operational surprises and losses*
- *Identifying and managing cross-enterprise risks*
- *Providing integrated responses to multiple risks*
- *Seizing opportunities*
- *Improving deployment of capital" (p.14-15).*

The COSO ERM Framework has eight Components and four objectives categories. It is an expansion of the COSO Internal Control-Integrated Framework published in 1992 and amended in 1994. In August 2004, the Treadway Commission's Committee of Sponsoring Organizations (COSO[3]) issued its Enterprise Risk Management-Integrated Framework after completing a development project spanning a three-year period. The eight components - additional components highlighted (COSO, 2004) - are:

- *"**Internal Environment** – The internal environment encompasses the tone of an organization, and sets the basis for how risk is viewed and addressed by an entity's people, including risk management philosophy and risk appetite, integrity and ethical values, and the environment in which they operate.*
- ***Objective Setting** – Objectives must exist before management can identify potential events affecting their achievement. Enterprise risk management ensures that Executive Summary management has in place a process to set objectives and that the chosen objectives support and align with the entity's mission and are consistent with its risk appetite.*
- ***Event Identification** – Internal and external events affecting achievement of an entity's objectives must be identified, distinguishing between risks and opportunities. Opportunities are channeled back to management's strategy or objective-setting processes.*
- ***Risk Assessment** – Risks are analyzed, considering likelihood and impact, as a basis for determining how they should be managed. Risks are assessed on an inherent and a residual basis.*
- ***Risk Response** – Management selects risk responses – avoiding, accepting, reducing, or sharing risk – developing a set of actions to align risks with the entity's risk tolerances and risk appetite.*
- ***Control Activities** – Policies and procedures are established and implemented to help ensure the risk responses are effectively carried out.*
- ***Information and Communication** – Relevant information is identified, captured, and communicated in a form and timeframe that enable people to*

[3] The Committee of Sponsoring Organizations (COSO) is a voluntary private-sector organization. COSO is dedicated to guiding executive management and governance entities toward the establishment of more effective, efficient, and ethical business operations on a global basis. It sponsors and disseminates frameworks and guidance based on in-depth research, analysis, and best practices.

carry out their responsibilities. Effective communication also occurs in a broader sense, flowing down, across, and up the entity.

- ***Monitoring*** *– The entirety of enterprise risk management is monitored and modifications made as necessary. Monitoring is accomplished through ongoing management activities, separate evaluations, or both."*

Moreover, ISO 31000 also provides a standard on the implementation of risk management published on the 13th of November 2009. The purpose of ISO 31000:2009 is to be applicable and adaptable for any institution. In Figure.1.1, ERM framework is shown.

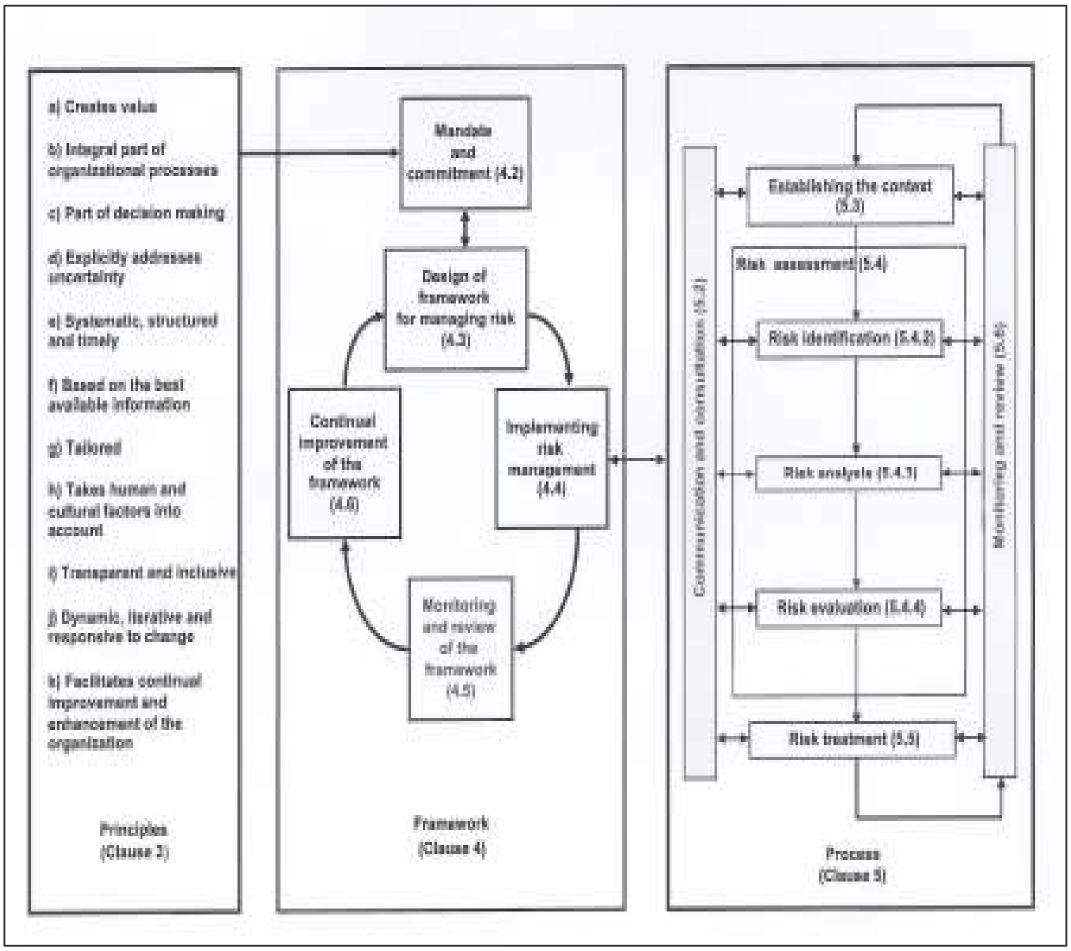

Figure 1.1 : Relationships between the risk management principles, framework and process (Source: ISO 31000, International Standard).

1.6 Risk Types

1.6.1 Market risk

Market risk is the risk that changes in market prices, interest rates, or other economic factors will cause a reduction in the value of an asset or portfolio of assets. Market risk can arise from open market positions or imperfectly hedged positions in which the correlations of offsetting positions are not perfectly negatively correlated.

Market risk factors can be classified under four main groups; interest rate risk, equity risk, currency risk and commodity risk. Risk management tools can be applicable to all these markets. To implement the market risk management tools, ERM framework should be applied. For this, risk identification and risk measurement are first stages. The correct risk measurement methodology selection is vital in risk measurement. Then the proper risk mitigation technique(s) should be chosen such as hedging, insurance or controlling.

1.6.2 Credit risk

It is the risk that financial losses are generated by counterparty failure to perform their obligations. In the last decades, the competition in business environment and economic crises increased the importance of credit risk management because many firms even a multinational financial institutions went bankruptcies. That's why, credit risk management is not only very vital for banks but also for all kinds of firms.

Generally, credit risk portfolio models have been developed by banks for regulatory reasons, capital allocation, derivatives pricing, and fund management. Popular models, CreditMetrics and Portfolio Manager based on multivariate normal distributions, Portfolio Risk Tracker (the most dynamics), CreditPortfolioView using econometric forecasting model and CreditRisk+ using an actuarial approach are being used in credit risk measurement.

1.6.3 Operational risk

Operational risk represents the risk of losses from failed system, processes and people and from events beyond the control of an organization. Some firms define operational risk as all risk that is not credit or market risk. Any risk developing from a breakdown in normal operations (e.g., system failures or processing mistakes), any risk from internal sources (e.g. internal fraud), excluding the impact of regulatory action or natural disasters and direct or indirect losses resulting from ineffective or insufficient systems, personnel, or external events (e.g., natural disasters or political events), excluding business risk can be described as operational risk. Internal sources of risk can be identified as fraud, mismanagement, nonadherence to policy, absence of standards and policies and error resulting from the direct or indirect actions of personnel. Some regulatory authorities suggest that reputational, strategic and legal risks should not be considered as an operational risk.

1.7 Risk Measurement Before VaR

1.7.1 Gap analysis

Gap analysis is very common approach even in nowadays and is developed by financial institutions to give a simple idea of interest rate risk exposure. Time horizon choice is very important criteria and the common period is one year. Determination of how much of the asset or liability portfolio will re-price within chosen period and the amount involved provides the rate-sensitive assets and rate-sensitive liabilities. The gap is the difference between these, and interest-rate exposure is taken to be change in net interest income that occurs in response to change in interest rates. It is fairly simple to carry out, but has its limitations: it only applies to on-balance sheet interest rate risk and even then only crudely; it looks at the impact of interest rates on income, rather than on asset or liability values; and results can be sensitive to the choice of horizon period.

1.7.2 Duration analysis

Duration analysis also used by financial institutions for measuring interest rate risk is very common method. The (Macaulay) duration D of a bond (or any other fixed-income security) can be defined as the weighted average term to maturity of the bond's cash flows, where the weights are present value of each cash flow relative to present value of all cash flows. Duration measure is useful because it gives an approximate indication of the sensitivity of a bond price to a change in yield. The bigger the duration, the more the bond price changes in response to a change in yield. This approach is very convenient because duration measures are easy to calculate and the duration of bond portfolio is a simple weighted average of the duration of the individual bonds in that portfolio. It is also better than gap analysis because it looks at changes in asset (or liability) values, rather than just changes in income. In spite of all these advantages, it has limitations like as gap analysis: they ignore risks other than interest rate risk, they are crude.

1.7.3 Scenario analysis

It is called as "what if" analysis in which different scenarios are set and investigated regarding gain/loss results. The most critical issue is to determine relevant variables (e.g. stock prices, interest rates, exchange rates, etc). For each scenario, the P/L, cash flows and/or accounting values of asset and liabilities should be studied and the results show the exposure.

Scenario analysis is not easy to carry out. The determination of right scenario and parameters is very difficult because the chosen scenarios should be reasonable and do not involve contradictory or excessively implausible assumptions and interrelationship between variables is also important.

1.7.4 Portfolio analysis

The analysis depends on portfolio's expected return and standard deviation as a measure of portfolio's risk. Other things being equal, an investor wants to a portfolio whose return has a high expected value and a low standard deviation. The investor should chose a portfolio that maximizes expected return for any given portfolio standard deviation or alternatively minimizes standard deviation for any given expected return. An investor who is very averse to risk will choose a safe portfolio with a low standard deviation and a low expected return and an investor who is less risk averse will choose a more risky portfolio with a higher expected return.

Portfolio theory says that correlation between assets in the portfolio has diminishing effects in risk due to diversification of the portfolio so the contribution of one asset into standard deviation of portfolio can be less than individual standard deviation of this asset.

Moreover, portfolio theory provides a useful framework for handling multiple risks and taking account of how those risks interact with each other. It is good in this respect for fund managers but there are some drawbacks. It is very difficult to calculate beta, which is equal to the covariance between return of individual asset and portfolio divided by the variance of the portfolio return. To estimate the beta coefficient properly, data on the returns to the new asset and the returns to all existing asset is needed to get the reliable results.

1.7.5 Derivative risk measures

The Greeks are vital tools in risk management. Each Greek measures the sensitivity of the value of a portfolio to a small change in a given underlying parameter, such as delta, gamma, vega, rho... etc. The Greeks in the Black–Scholes model are relatively easy to calculate, a desirable property of financial models, and are very useful for derivatives traders, especially those who seek to hedge their portfolios from adverse changes in market conditions. Delta, gamma and vega are well-defined for measuring changes in Price, Time and Volatility, respectively. Although rho is a primary input into the Black–Scholes model, the overall impact on the value of an option corresponding to changes in the risk-free interest rate is generally insignificant and therefore higher-order derivatives involving the risk-free interest rate are not common.

Using these measures, it should be kept in mind that they make sense only within the confines of a dynamic hedging strategy: the measures, and the resulting hedge positions, only work against small changes in risk factors and only then if they are revised sufficiently frequently. There is always a worry that these measures and their associated hedging strategies might fail to cover the investor against major market moves such as stock market or bond market crashes or a major devaluation.

2. ENERGY RISK MANAGEMENT

2.1 Energy Risk Management

Energy is a very risky business. Energy related human risks include the possibility of accidents having health and safety issues. A nuclear power plant melt down, Chernobyl disaster occurred on 26 April 1986; an oil spill, BP Deepwater Horizon oil spill in 2010 and LNG explosion, Cleveland East Ohio Gas Explosion in 1944 are important energy risk for human beings. In addition to catastrophic risks, energy companies have financial risks such as losses in real assets from falling crude oil prices, rising drilling ring costs, a refinery fire, increasing environmental regulations on gasoline.

Jorion (1997) summarized financial risks of energy companies under 5 main groups;

- Market risks due to price changes of financial assets and liabilities
- Credit risk due to defaults on contractual obligations
- Liquidity risk due to the lack of market activity or the failure to meet a cash flow obligation
- Operational risk due to fraud and technical problems with financial trading systems
- Legal risk due to noncompliance with the law or adverse regulatory changes

2.2 Financial Risks in Energy Markets

2.2.1 Price risk

It is also called as market risk and the risk of losing money due to price movements in the energy markets. Energy companies will lose money if the commodity prices go down and the oil consumers obviously lose money if the prices go up. Due to high volatility in the prices of oil derivatives, the price risk cannot be disregarded by energy companies.

2.2.2 Credit risk

Credit risk is the risk of financial losses due to the inability in payment of counterparty's obligation. Globally, credit risk for energy companies implies the counterparty's contract default. The credit crunch in U.S. energy sector after Enron bankruptcy has alerted energy traders to consider their credit policies and develop credit risk management process. In Turkey, most oil companies do not own stations. The credit risk of these stations is not negligible due to the low collateral ratio.

2.2.3 Liquidity risk

This risk comes from illiquidity of energy derivatives markets. Under economic crises or unexpected circumstances such as Gulf War, the volatility of energy derivative commodity prices becomes very high and this leads to illiquidity of energy markets in which oil traders could not give a bid or offer price. Companies which face to illiquid markets have to close their positions with high costs or they meet the claims of their contracts.

2.2.4 Cash-flow risk

This is the risk that a company will not be able to produce cash to meet its payments either for energy derivatives or operational costs. It is especially important for airlines companies. Previously mentioned Metallgessellschaft AG case is a good example for liquidity and cash-flow risk.

2.2.5 Basis risk

Basis risk is the risk of loss due to adverse move or the breakdown of expected differentials between two prices. It is important especially in hedging because derivative contract to be able to use hedge the portfolio move up or down in sync with the value of underlying commodity. Bad weather conditions, political developments, changes in regulations, catastrophic events increases basis risk between commodity and its derivatives' prices. In hedging, the basis risk should be mainly considered. Ideal derivatives contract is one that has a zero risk or the lowest basis risk with the energy price from which hedge is needed. The larger the basis risk, the less efficient derivative is to hedge the portfolio.

Futures contracts traded on exchanges such as Intercontinental Exchange (ICE), the New York Mercantile Exchange and the Tokyo Commodity Exchange all have their pricing references and terms fixed in their regulations. When their pricing reference does not match the underlying physical exposure, the basis risk occurs.

2.2.5.1 Locational basis

Locational basis risk occurs when the derivative contract is pricing against the same energy contract but in a different geographic region. Demand and supply factors, political tension and problems, pipeline problems affect the price of physical product and its derivative prices. This creates basis risk between the same European and Nymex gasoil.

2.2.5.2 Time basis

Sudden shift in demand and transportation problems lead to increase time basis risk in energy markets. Natural gas prices are the most sensitive ones toward price movements and they are affected by time basis due to seasonality. The most of energy firms hedge their positions regarding their needs and seasonality.

2.2.5.3 Mixed basis risk

Mixed basis risk can comprise of product and time basis. It occurs when the underlying position is hedged with one derivative which is not match with underlying and time basis. For example, January gasoline cargo is hedged with a June Fuel oil swap. It has time and product basis exposures.

2.3 Oil Price Determinants

Every sector in an economy directly or indirectly depends on petroleum. Moreover, as integration of financial and oil sectors, economy and oil prices affect each other in both dimensions. Therefore, changes in petroleum market and petroleum prices cause various impacts on both national and world economies through chain reactions.

Different from other commodities, such as currency, energy markets are concerned with bulky and dangerous and they must be transported over vast distances, which are the most politically unstable regions of the world. Weather, political tension, the balance of supply and demand, OPEC decisions[4], changes to tax and legal systems are oil price determining factors. Due to instabilities in all these, the volatility of oil prices is very high and sudden price movements from one day to the next. In Figure 2.1, the effects of political factors on oil prices can be easily seen.

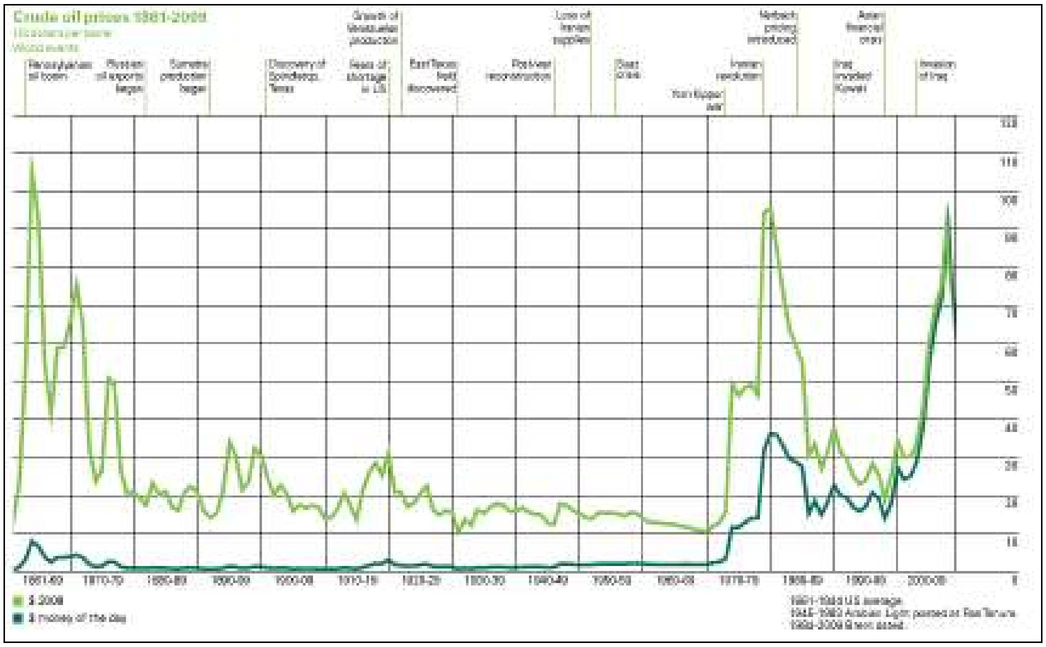

Figure 2.1 : Crude Oil Prices 1861-2009 and History (BP Statistical Review of World Energy June 2010, Url-1).

There are six main factors that are very influential in the price of crude oil; supply/demand, quality (refining cost and yield), location (transportation), reliability (production rate), availability (reserves) and exploration and development (costs and quality of wells) (Maduekwe, 2004 and Alhajji, 2001). Supply and demand relationship is cyclic and very complex. The cost to refiner for the process affects the price in quality view. Location is influential in transportation cost to move crude oil and petroleum products from the point of production/refining to the customer.

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[4] Pls see further information about modelling of the oil marker on the paper submitted by De´esa, Karadelogloua, Kaufmannb, Sa´ nchez (2005). Modelling the world oil market: Assessment of a quarterly econometric model. Energy Policy 35 (2007) 178–191. The paper advocates that *“Oil demand depends on domestic economic activity and the real price of oil. Oil supply for non-OPEC producers, based on competitive behaviours, is constrained by geological and institutional conditions. Oil prices are determined by a ‘‘price rule’’ that includes market conditions and OPEC behaviour. Policy simulations indicate that oil demand and non-OPEC supply are rather inelastic to changes in price, while OPEC decisions about quota and capacity utilisation have a significant, immediate impact on oil prices.”*Moreover, Chevillon and Rifflart (2009) analyzed the determinants of the real price of crude oil. Pls see further information about OPEC roles in price their paper named “Physical market determinants of the price of crude oil and the market premium”.

Production rate and production capacity controlling the reliability and availability are controlled by reserves. Production capacity determined by exploration and development affects prices in the short term whereas reserves affect prices in the long term.

The Arab embargo on oil exports in 1973 and the fall of Shah Iran in 1978, which are the oil shocks changed the pattern of cheap oil. By Arab embargo, oil prices raised five fold. In 1978, prices soared to \$80-\$100 a barrel (bbl)[5] in today's prices.

In the last two decades, two co integrating relations affect the changes in oil prices: OPEC's behavior and the coverage rate of OECD expected future demand using inventory behaviors (Chevillion and Rifflart, 2009). How does OPEC affect the prices? OPEC attempts to control prices using its market power and quato. The question comes to minds is what OPEC is.

The Organization of the Petroleum Exporting Countries (OPEC) established in 1960 is a strong cartel dominates oil markets by oligopolistic behavior which has been a considerable political and economical force in the market. Two thirds of the world's oil reserves belong to OPEC members. When the oil prices over the past years are analyzed, it can be realized that OPEC is responsible for most of the price increases due to their production limitation cuts and market power (Chevillion and Rifflart, 2009).

Many mathematical models are developed to explore the objective function of OPEC, which includes economic and political considerations (Chevillion & Rifflart, 2009 and Kiswani, 2009, De´esa, Karadelogloua, Kaufmannb, Sa´ nchez, 2005). OPEC members consider both the political support of their citizens and profits when determining oil extraction rates.

2.3.1 Oil specifications

Petroleum is one of the energy resources in human lives. Petro means rock, and oleum means oil. In it strictest sense, petroleum includes only crude oil.

[5] Barrel is the English unit of crude oil measurement and holds 42 U.S. gallons or 34.97 Imperial gallons.

Typical crude oil consists of five chemicals. The compositions are (Hyne, 2001);

Carbon	84-87 %
Hydrogen	11-14 %
Sulfur	0.06-2 %
Nitrogen	0.1-2 %
Oxygen	0.1-2 %

Due to above composition, crude oil is called hydrocarbons.

2.3.2 °API

Crude oil compared and described by density. °API is the most common used density scale and stands for the American Petroleum Institute, based in Washington, D.C.

°API can be calculated as;

$$°API = [(141.5/\text{specific gravity at } 60°F)-131.5]$$

The °API of crude oils varies from 5 to 55. As the degree increases, the viscosity increases. Heavy oils are below 25 and light oils are 35 to 45. Average weight crude oils are 25 to 35. Light oils are transparent and fluid, whereas heavy oils are viscous and dark colored. Light oils are highly valuable, on the other hand, heavy oils are less valuable (Hyne, 2001).

2.3.3 Sulfur

The other important chemical in oil that determines its quality is sulfur. With the increasing environmental concern, the least amount of sulfur contained oil is much more desirable because sulfur is burned; it forms sulfur dioxide, which causes air pollution and acid rains. As the crude oil is being processed, the sulfur inside of oil is removed in refinery process. Sulfur content of oil determines the classification of oil as sweet, which has less than 1 % sulfur by weight and sour which has more than 1% sulfur. Heavy oils tend to be sour, whereas light oils tend to be sweet. Intermediate sulfur crude has 0.6 to 1.7% sulfur (Hyne, 2001).

2.3.4 Benchmark crude oils

There exist several reference/benchmark crude oil prices which refers to an oil of high quality with a specific production or trading location in world exchanges: The main benchmark crude oils are West Texas Intermediate (WTI), West Texas Sour, Brent and Dubai.

Benchmark Crude Oil	**Area**	**°API**	**Sulfur Concentr.**
WTI	United States	38 to 40	0.3%
West Texas Sour	United States	33	1.6%
Brent	North Sea	38	0.3%
Dubai	Middle East	31	2%

Dubai and the WTI prices are mainly traded in the United States and Asia, whereas the North Sea Brent is often used as the world reference. In the London based IntercontinentalExchange (ICE) Futures formerly known as the International Petroleum Exchange (IPE), the Brent is used to specify the price of two thirds of crude oil exchanged worldwide.

Crude stream is oil purchased from an oil-exporting country. Crude streams are Arabian light (Saudi Arabia), Bachequero (Venezuela), Bonny light (Nigeria), Brass River (Nigeria), Dubai (Dubai), Ekofisk (Norway), Iranian light (Iran), Kuwait (Kuwait), North Slope (USA) (Hyne, 2001).

2.3.5 World oil demand

The demand for OPEC crude in 2010 is estimated at 28.7 Millions of Barrels per Day(mb/d). In 2011, the demand for OPEC crude is expected to average 28.9 mb/d, about 0.2 mb/d up from 2010 (Table 2.1).

Table 2.1 : World oil demand forecast for 2010, mb/d (OPEC, Monthly Oil Market Report, August 2010).

	2009	1Q10	2Q10	3Q10	4Q10	2010	Change 2010/09 Volume	%
North America	23.29	23.59	23.47	23.64	23.79	23.62	0.33	1.41
Western Europe	14.52	14.09	13.84	14.17	14.31	14.11	-0.41	-2.83
OECD Pacific	7.66	8.23	7.35	7.18	7.94	7.67	0.02	0.24
Total OECD	**45.47**	**45.92**	**44.66**	**45.00**	**46.04**	**45.40**	**-0.06**	**-0.14**
Other Asia	9.83	9.95	10.14	9.98	10.15	10.05	0.23	2.30
Latin America	5.88	5.78	6.01	6.17	6.15	6.03	0.15	2.59
Middle East	7.09	7.18	7.25	7.52	7.26	7.30	0.22	3.07
Africa	3.25	3.30	3.30	3.20	3.33	3.28	0.04	1.17
Total DCs	**26.04**	**26.21**	**26.71**	**26.87**	**26.89**	**26.67**	**0.63**	**2.43**
FSU	3.97	3.95	3.74	4.17	4.22	4.02	0.05	1.17
Other Europe	0.73	0.70	0.67	0.69	0.75	0.70	-0.02	-2.92
China	8.25	8.23	8.77	9.08	8.73	8.70	0.45	5.46
Total "Other Regions"	**12.95**	**12.88**	**13.19**	**13.94**	**13.69**	**13.43**	**0.48**	**3.68**
Total world	**84.46**	**85.01**	**84.56**	**85.81**	**86.62**	**85.50**	**1.05**	**1.24**
Previous estimate	84.41	84.76	84.40	85.73	86.52	85.36	0.95	1.12
Revision	0.04	0.24	0.16	0.08	0.10	0.14	0.10	0.12

2.3.6 World oil supply

Global oil supply increased 0.81 mb/d in July to average 86.36 mb/d. Non-OPEC supply experienced growth of 0.69 mb/d while OPEC crude production increased by 0.12 mb/d (Figure 2.2). The share of OPEC crude oil in global production remained steady at 34% in July.

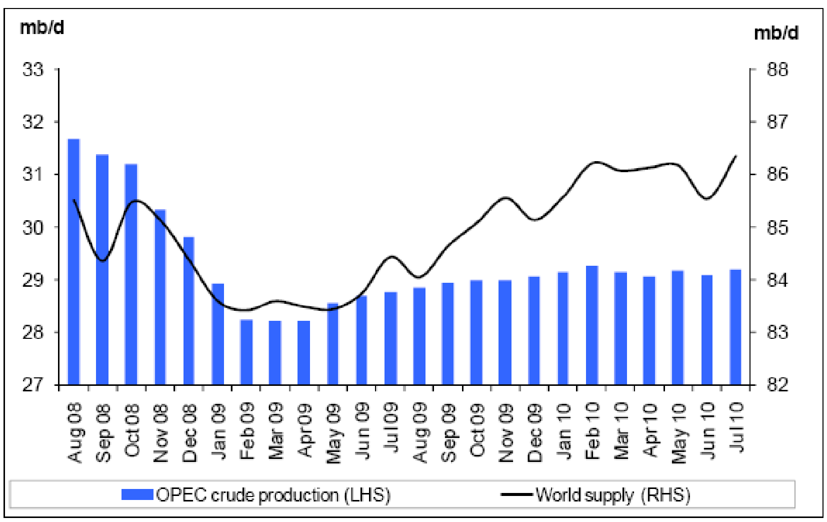

Figure 2.2 : OPEC and World oil supply (OPEC, Monthly Oil Market Report, August 2010).

2.3.7 World oil proved reserves

Table 2.2 : World proved reserves (BP Statistical Review of World Energy, June).

Proved reserves

		At end 1989	At end 1999	At end 2008	At end 2009			
		Thousand million barrels	Thousand million barrels	Thousand million barrels	Thousand million tonnes	Thousand million barrels	Share of total	R/P ratio
Total North America		97,9	69,5	73,4	**10,2**	**73,3**	5,5%	15,0
Total S. & Cent. America		69,5	97,8	198,9	**28,5**	**198,9**	14,9%	80,6
Total Europe & Eurasia		84,2	107,8	137,2	**18,5**	**136,9**	10,3%	21,2
Total Middle East		661,0	685,8	753,7	**102,0**	**754,2**	56,6%	84,8
Total Africa		59,1	84,7	127,5	**16,9**	**127,7**	9,6%	36,0
Total Asia Pacific		34,7	39,9	41,7	**5,6**	**42,2**	3,2%	14,4
Total World		**1006,4**	**1085,6**	**1332,4**	**181,7**	**1333,1**	**100,0%**	**45,7**
of which:	European Union	7,7	9,0	6,1	**0,8**	**6,3**	0,5%	8,2
	OECD	116,4	93,3	91,3	**12,4**	**90,8**	6,8%	13,5
	OPEC	763,2	831,9	1028,8	**140,4**	**1029,4**	77,2%	85,3
	Non-OPEC‡	175,8	166,4	180,6	**24,6**	**180,9**	13,6%	14,7
	Former Soviet Union	67,3	87,2	123,0	**16,7**	**122,9**	9,2%	25,5
Canadian oil sands•		n/a	163,3	143,3	**23,3**	**143,3**		
Proved reserves and oil sands		n/a	1248,9	1475,7	**205,0**	**1476,4**		

More than 100 years.
Less than 0.05.
Less than 0.05%.
Excludes Former Soviet Union.
'Remaining established reserves', less reserves 'under active development'.

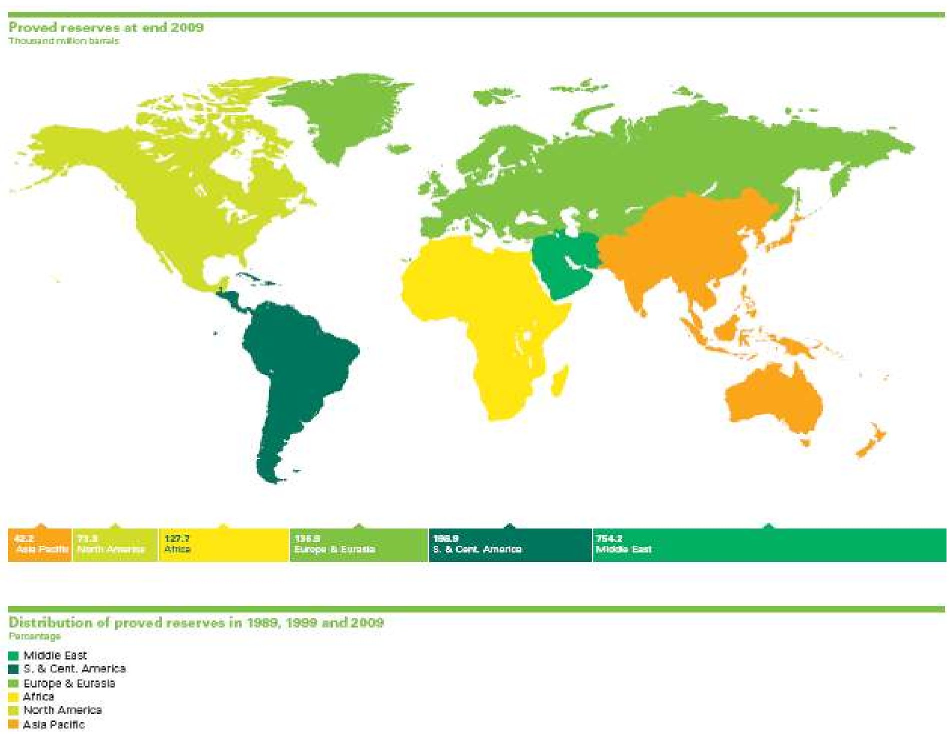

Figure 2.3 : World proved reserves (BP Statistical Review of World Energy, June 2010).

2.3.8 World oil production & consumption

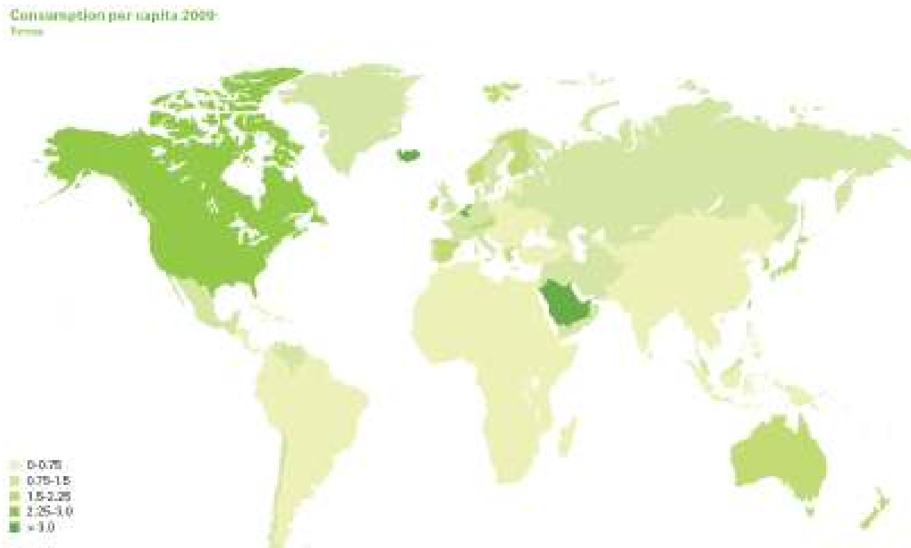

Figure 2.4 : World oil consumption (BP Statistical Review of World Energy, June 2010).

Supply and demand, reserves (availability) are main important factors forming price of oil. The limited reserves and the restriction in supply are contributing factors in price increases.

Table 2.3 : World oil production and consumption (Statistical Review of World Energy, June 2010).

Production*

Thousand barrels daily		1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	**2009**	Change 2009 over 2008	2009 share of total
Total North America		13.678	13.904	13.906	14.069	14.193	14.137	13.696	13.732	13.638	13.169	**13.388**	1,6%	16,5%
Total S. & Cent. America		6.699	6.813	6.722	6.619	6.314	6.680	6.899	6.866	6.636	6.678	**6.760**	1,2%	8,9%
Total Europe & Eurasia		14.480	14.950	15.450	16.289	16.973	17.579	17.541	17.595	17.810	17.572	**17.702**	0,8%	22,4%
Total Middle East		22.328	23.475	23.025	21.729	23.299	24.797	25.258	25.497	25.156	26.182	**24.357**	-7,3%	30,3%
Total Africa		7.583	7.804	7.897	7.990	8.386	9.324	9.921	9.925	10.238	10.219	**9.705**	-5,2%	12,0%
Total Asia Pacific		7.556	7.874	7.813	7.836	7.750	7.853	7.946	7.942	7.968	8.175	**8.036**	-1,9%	10,0%
Total World		**72.325**	**74.820**	**74.813**	**74.533**	**76.916**	**80.371**	**81.261**	**81.557**	**81.446**	**81.995**	**79.948**	**-2,6%**	**100,0%**
of which:	European Unio	3.684	3.493	3.285	3.339	3.128	2.902	2.659	2.422	2.388	2.222	**2.082**	-6,1%	2,6%
	OECD	21.103	21.521	21.303	21.430	21.165	20.766	19.861	19.458	19.140	18.414	**18.390**	-0,2%	22,5%
	OPEC	29.646	31.072	30.544	29.132	30.877	33.592	34.721	34.920	34.604	35.568	**33.076**	-7,3%	41,2%
	Non-OPEC‡	35.127	35.734	35.608	35.869	35.540	35.371	34.700	34.321	34.046	33.602	**33.671**	0,1%	41,9%
	Former Soviet	7.552	8.014	8.660	9.533	10.499	11.407	11.839	12.316	12.795	12.825	**13.202**	3,0%	16,9%

* Includes crude oil, shale oil, oil sands and NGLs (the liquid content of natural gas where this is recovered separately).Excludes liquid fuels from other sources such as biomass and coal derivatives.

◆ Less than 0.05%.

‡ Excludes Former Soviet Union.

Note: Growth rates are adjusted for leap years.

Consumption*

Thousand barrels daily		1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	**2009**	Change 2009 over 2008	2009 share of total
Total North America		23.286	23.548	23.571	23.665	24.050	24.898	25.023	24.904	25.020	23.795	**22.826**	-4,7%	26,4%
Total S. & Cent. America		4.905	4.855	4.916	4.913	4.754	4.871	5.047	5.210	5.533	5.681	**5.653**	-0,8%	6,6%
Other Europe & Eurasia		448	417	445	469	493	502	540	549	582	592	**580**	-2,0%	0,7%
Total Europe & Eurasia		19.760	19.577	19.766	19.760	19.940	20.139	20.301	20.498	20.203	20.193	**19.372**	-4,2%	23,5%
Total Middle East		4.689	4.838	4.979	5.164	5.394	5.706	6.010	6.247	6.469	6.864	**7.146**	3,8%	8,7%
Total Africa		2.490	2.484	2.517	2.552	2.614	2.691	2.800	2.786	2.931	3.045	**3.082**	1,1%	3,7%
Total Asia Pacific		20.518	21.126	21.282	21.891	22.671	23.957	24.331	24.721	25.462	25.662	**25.998**	1,0%	31,1%
Total World		**75.648**	**76.428**	**77.032**	**77.945**	**79.424**	**82.261**	**83.513**	**84.367**	**85.619**	**85.239**	**84.077**	**-1,7%**	**100,0%**
of which:	European Unio	14.814	14.692	14.861	14.797	14.868	15.032	15.204	15.260	14.926	14.775	**14.143**	-4,4%	17,3%
	OECD	47.469	47.653	47.692	47.676	48.277	49.073	49.489	49.323	49.008	47.353	**45.327**	-4,8%	53,4%
	Former Soviet	3.714	3.631	3.646	3.688	3.769	3.815	3.798	3.948	3.973	4.115	**3.965**	-4,0%	4,7%
	Other EMEs	24.465	25.144	25.694	26.581	27.377	29.374	30.226	31.096	32.639	33.771	**34.785**	2,8%	41,9%

* Inland demand plus international aviation and marine bunkers and refinery fuel and loss. Consumption of fuel ethanol and biodiesel is also included.

◆ Less than 0.05%.

Notes: Annual changes and shares of total are calculated using million tonnes per annum figures.

Growth rates are adjusted for leap years.

2.4 Oil price risk

The boom of West Texas Intermediate (WTI) to $147/barrel in early July 2008 and its collapse to under $34/barrel five months later surprised many people and showed the volatility of oil prices (Figure 2.5). In the last decade, due to the high liquidity, hedge funds preferred to invest oil derivative products such as oil futures contract so the price also has been affected by these funds speculative movements deeply. Moreover, cold winters or natural disasters can lead to an unexpected increases in demand or decrease in the supply of oil products and a subsequent sharp increase in prices. Political instability in oil-exporting countries accounts for the additional variances in oil prices. Sudden changes in oil prices have contributed to a climate of uncertainty for energy companies and investors and a climate of distrust among consumers and regulators. Whatever the adverse effects of oil price volatility, it seems likely that oil prices will remain volatile in the foreseeable future. Many factors have been put forward to explain these extreme movements in oil prices, such as political decisions, OPEC quotas, weather conditions, armed conflicts, speculation, structural changes in demand for diesel and gasoline and many other factors. Moreover, liberalization of trading markets and development of transaction tools such as derivatives and information technology seem only to further intensify volatility.

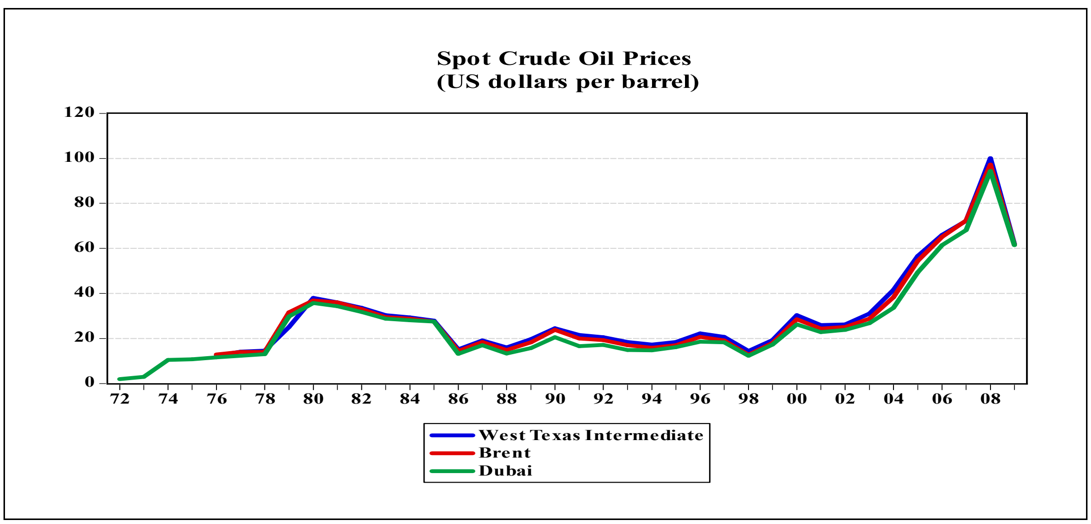

Figure 2.5 : Spot crude prices (BP Statistical Review of World Energy, June 2010-Source:Platts).

In financial markets, volatility, in statistics known as standard deviation (squared root of variance), means price risk. The higher the volatility, the higher the price risk is. Price risk is a loss due to depreciation in the value of market risk factors. One of the most important risk factors is commodity (oil) price risk. Oil price risk is the risk of loosing money due to price movement in two dimensions either in up or down. Producers and distributors who have stock capacity will lose money when the prices go down and the users will lose when the prices go up.

All risks in energy market are correlated and they affect each other in all dimensions (James, 2008). All above mentioned factors that are influential in oil prices, increases price risks due to increasing volatility. It is impossible to mitigate price risk effectively without measuring it correctly. After the proper methodology selection, the risk mitigating techniques and instruments should be chosen.

2.4.1 Oil price for energy companies

Energy companies have to carry stock either for obligation or survival of their business continuity. Due to having long position, these companies are exposed to price risk. Stock keeping days, the stock amount and the price decreases are the important factor in affecting oil price impact into the companies.

Let's see the oil price risk effects on oil distributors in Turkey. In the scenario analysis, the long positions of oil distributors are stressed by the worst price drop in the last two years. The Platts commodity prices are given in Table.2.4. The worst price drop from September 2008 to October 2008 is above 30 % as seen as Table.2.5 The stock amounts are assumed as the average monthly sales amount. The yearly sales amount are taken from 2009 Oil Sales Report declared by Energy Market Regulatory Authority (EMRA) and average monthly sales are applied to the October 2008 price drop. It is seen that the first five biggest oil distributors of Turkey can be lost 342 Million USD as total for one month if they do not hedge their hedgeable stocks (Table 2.6).

Table 2.4 : Platts and ICE commodity prices (Platts and ICE,Url-13-3 respectively).

Date	Gasoil	Gasoline	Fuel oil	Jet	Brent	ICE Gasoil	ICE Brent
31.10.2007	$821	$806	$475	$861	$90	$787	$91
30.11.2007	$827	$777	$439	$847	$88	$793	$88
31.12.2007	$845	$862	$453	$883	$96	$839	$94
31.01.2008	$816	$779	$423	$844	$92	$797	$92
29.02.2008	$944	$870	$466	$978	$101	$915	$100
31.03.2008	$991	$924	$487	$1.051	$103	$969	$100
30.04.2008	$1.106	$972	$500	$1.148	$110	$1.073	$111
30.05.2008	$1.220	$1.132	$555	$1.259	$128	$1.188	$128
30.06.2008	$1.287	$1.180	$679	$1.335	$139	$1.263	$140
31.07.2008	$1.153	$1.029	$665	$1.226	$124	$1.128	$124
29.08.2008	$1.048	$1.003	$644	$1.117	$114	$1.030	$114
30.09.2008	$938	$836	$559	$940	$94	$915	$98
31.10.2008	$654	$509	$254	$673	$61	$637	$65
28.11.2008	$542	$410	$189	$549	$49	$526	$53
31.12.2008	$430	$325	$147	$437	$37	$419	$46
30.01.2009	$462	$456	$256	$466	$44	$450	$46
27.02.2009	$389	$424	$229	$402	$45	$387	$46
31.03.2009	$430	$459	$252	$445	$47	$420	$49
30.04.2009	$433	$508	$280	$451	$50	$428	$51
29.05.2009	$525	$651	$365	$557	$65	$523	$66
30.06.2009	$563	$655	$388	$594	$68	$557	$69
31.07.2009	$573	$706	$410	$599	$70	$571	$72
28.08.2009	$594	$680	$430	$628	$73	$597	$73
30.09.2009	$554	$611	$397	$589	$66	$552	$69
30.10.2009	$631	$700	$445	$654	$75	$625	$75
30.11.2009	$624	$701	$449	$656	$77	$614	$78

Table 2.5 : The Worst Platts prices.

		Gasoil	Gasoline	Fuel oil	Jet
30.09.2008	Prices in USD	938	836	559	940
31.10.2008	Prices in USD	654	509	254	673
30.09.2008	% of Return/Loss	-10%	-17%	-13%	-16%
31.10.2008	% of Return/Loss	-30%	-39%	-55%	-28%
30.09.2008	Return/Loss in USD	-110	-168	-85	-177
31.10.2008	Return/Loss in USD	-284	-327	-305	-268

Table 2.6 : The Loss at worst case scenario which comes from the historical occurrence on October, 2008.(EMRA, Url-2).

Distributor Company	Commodity	2009 Sales Amount (ton)	2009 Total Sales Amount (ton)	Market Share	Average Sales Amount for One Month	Loss (Million USD) at The Worst Scenario*	Total Loss (Million USD)
Petrol Ofisi A.Ş.	Gasoline	521.687	4.699.245	27%	43.474	(-14)	(-114)
	Gasoil	3.618.292			301.524	(-86)	
	Fuel oil	547.139			45.595	(-14)	
	Other	12.127			1.011	(-)	
Shell & Turcas Petrol A.Ş.	Gasoline	629.885	3.268.600	19%	52.490	(-17)	(-80)
	Gasoil	2.579.761			214.980	(-61)	
	Fuel oil	58.335			4.861	(-1)	
	Other	649			54	(-)	
Opet Petrolcülük A.Ş.	Gasoline	364.218	3.099.556	18%	30.352	(-10)	(-75)
	Gasoil	2.208.525			184.044	(-52)	
	Fuel oil	500.353			41.696	(-13)	
	Other	26.460			2.205	(-1)	
BP Petrolleri A.Ş.	Gasoline	327.665	1.991.165	11%	27.305	(-9)	(-49)
	Gasoil	1.502.975			125.248	(-36)	
	Fuel oil	159.529			13.294	(-4)	
	Other	996			83	(-)	
Total Oil Türkiye A.Ş.	Gasoline	128.741	1.018.245	6%	10.728	(-4)	(-25)
	Gasoil	778.746			64.896	(-18)	
	Fuel oil	109.592			9.133	(-3)	
	Other	1.168			97	(-)	
Others	Total		3.510.050	20%	292.504	(-83)	(-83)
Total	Gasoline	2.187.892	17.586.861	100%	182.324	(-60)	(-427)
	Gasoil	13.714.924			1.142.910	(-324)	
	Fuel oil	1.638.192			136.516	(-42)	
	Other	45.853			3.821	(-1)	

2.5 Corporate Risk Management

Risk management consists of the identification, assessment, and prioritization of risks as defined in ISO 31000 and COSO mentioned previous section followed by application of resources to monitor, minimize, and control the probability and/or impact of events regarding upside potentials. Mitigation strategies to manage risk include transferring the risk to another party, avoiding the risk, reducing the negative effect of the risk by controlling, and accepting the risks. Hedging is one of the most important risk mitigation techniques. Hedging is the taking position established in one market in an attempt to offset exposure to price changes or fluctuations in some opposite position to mitigate the risk. Energy derivatives such as forwards, futures, options and swaps are used for many purposes: hedging, speculation and arbitrage. In hedging, the direction of position, the size and the instruments are important decision making criteria. Wang (2007) examines corporate risk management practice and tries to find out why firms manage their risks and how they manage them.

2.6 Hedging

Energy companies have a concern about one issue: in the face of multi-period, possibly multi-commodity, price and quantity uncertainty, what the optimal hedge ratios should be to protect the firm from potential downside risk? While companies are naturally interested in minimizing downside risk, how can they also take the notion of upside capture into account? Although hedging activities are costly, why should the energy companies hedge their portfolios? Which instruments should be used?

Solutions depend on the hedgeable portfolio and risk appetite of the company. Generally option and futures derivatives are more liquid than swaps and forwards. Whereas futures are costless-to-enter due to financial leverage, they eliminate both downside risk as well as upside potential. On the other hand, options are costly, but they keep upside potential while mitigating downside risk. After the decision of proper hedging instrument, the determination of optimal hedge ratio is the subsequent vital step in hedging.

The concern with why firms hedge even when hedging activities are costly is very common. The reasons frequently cited consist of reduction in the firm's stock price sensitivity to oil and gas prices(Jin and Jorion, 2006), decreasing a firm's expected tax payments, reducing the costs of financial distress, allowing firms to better plan for their future capital needs and reduce their need to gain access to outside capital markets, improving the design of management compensation contracts and allowing firms to evaluate their top executives more accurately and improving the quality of the decisions made (Kolos, 2005). Kolos assumed that the corporation has made an affirmative decision to manage its risk, without requiring us to specify the firm's motivation for doing so. Moreover, Kolos suggested that the issue of the hedge implementation has been picked up by financial engineering, which deals with the mechanics of using financial contracts to implement the hedge. The instrument selection is also controversial. Whereas futures are considered as costless-to-enter, they eliminate both downside risk as well as upside potential. In contrast, options are costly, but they preserve upside potential while eliminating downside risk. In addition to all these, Kolon also addresses variance-minimization, or mean-variance efficiency. Minimum-variance as a measure of portfolio risk and the use of minimum-variance hedging as a method of minimizing is widely used by practitioners (Miffre, 2004; Terry, 2005; Kavussanos and Nomikos, 2000). In this approach, risk is defined only in terms of standard deviation; hence whether or not asset returns being skewed or leptokurtic does not affect investors' utility. In fact, short-horizon financial asset returns are characterized by both skewness and leptokurtosis. Minimum-variance hedging will not produce a hedge portfolio with minimum risk. The main concern about minimum-variance hedging approach is that it could not decrease risk by decreasing standard deviation. Harris and Shen (2006) study the consequences of minimum-variance hedging in two alternative frameworks that implicitly incorporate portfolio; VaR and CVaR. The VaR of normally distributed returns having zero mean return results from a constant multiple of the standard deviation of the portfolio. In this case, minimizing variance leads to decrease VaR as the same proportion. However, when the return distribution is nonnormally distributed, the standard deviation is not only parameter to calculate the VaR of a portfolio. In addition to standard deviation, the portfolio' skewness and kurtosis should be added in the determination of VaR. VaR is the most common used risk measurement tool in financial and energy markets as mentioned on the next chapter. The studies of VaR in using asset allocation and performance evaluation suggested to use VaR instead of standard deviation minimization (Alexander and Bapista, 2002, 2007; Campbell, Huisman and Koedijk, 2001; Topaloglou, Vladimirou, Zenios, 2002). Alexander and Baptista (2004) compare minimum VaR and examine the impact of VaR constraints in the mean-variance model.

Harris and Shen (2006) study two issues. The first is whether the substantial reduction in portfolio standard deviation that can be gained from minimum-variance hedging offers a similarly large reduction in portfolio VaR and CVaR (Cash Flow VaR). The concern that minimum-variance hedge portfolios are constructed and the percentage reduction in standard deviation is compared with the percentage reduction VaR and CVaR is studied by empirical research with the use of data on 20 cross-hedged developed-market currency portfolios. The study concludes that minimum variance hedging yields a reduction in both VaR and CVaR which is about 80% of the reduction in standard deviation, implying that minimum-variance hedge portfolios are riskier than conventional measures of risk would imply[6]. In some

[6] Pls see the summarized the principles of minumum-variance hedging and derivation of expressions for the standard deviation, skewness and kurtosis of minumum variance hedge portfolio in the study of

cases, the differences can be substantial. Moreover, Harris and Shen (2006) insist on the VaR minimization for optimal hedge ratio decision regarding the VaR usage in the determination of traders' limits on their investments.

2.7 Energy Derivatives

An energy derivative is a contract which is derived from underlying energy related commodity such as gasoil, gasoline, crude oil, electricity and natural gas. Energy derivative contract is an agreement about tradeable commodity at determined future date or to exchange cash flows based on energy prices at determined future dates. Energy derivatives are forwards, futures, options and swaps like as in financial markets. The most common used energy derivatives are futures and options. Options in energy markets have a very long history. Especially before the liberalization of energy markets, being optional was very important to be able to react to fluctuations in consumption, interruptions in transmissions or power plant outages.

Forwards, futures and swaps are hedging instruments which are not optional. In spite of their being strict, they are the most liquid type of derivatives. The using and pricing of option are more difficult compared to forward, futures and swaps (Burger, 2007).

2.7.1 Forwards

Forward contracts are bilateral agreements to purchase or sell a certain amount of a commodity on a delivery date at a predetermined contract price (Figure 2.6). The seller of a forward contract is under the obligation of delivering the commodity on the determined date and the buyer of a forward contract is under the obligation of taking the commodity on the determined date. The delivery date, the price at the delivery, the amount of commodity is specified in the agreement. The payment date in the contract is usually at the delivery date or very near to it. The current forward price has the time parameter; at time t and a given delivery date T. If the contract is closed before the delivery date T, the contract has a positive or negative fair value depending on the commodity prices. The fair value is the price of contract which a neutral market participant will buy or sell the contract.

Harris,R.&Shen,J.(2006), "Hedging and Value at Risk", The Journal of Futures Markets, Vol.26., pg 373-377.

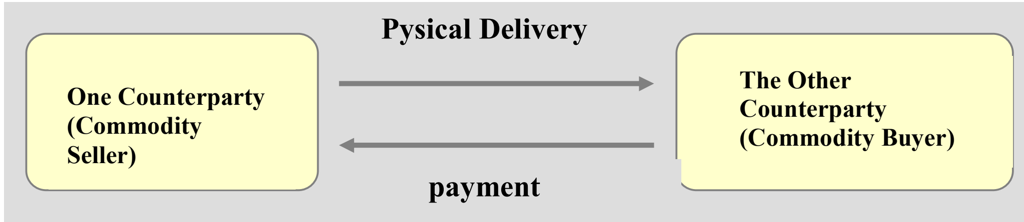

Figure 2.6 : Commodity forward contract.

2.7.1.1 Commodity forward contract

Forward contracts are over the counter (OTC) trades, executed through brokers. Different from financial forward contracts, for crude oil or electricity in some regions, there exists a fairly liquid market of standardized forward contracts. Different from classical forward agreement, in this type of forward contract, it is possible to close the position by executing an opposite trade with a different counterparty. Classical forward agreements are tailor made trades and very difficult to revise them later.

Credit risk of counterparties is the most important disadvantages. Credit risk includes the inability in one of the counterparties cannot fulfill his obligation to delivery or pay the commodity.

There are many purposes of using forward agreements; for hedging, for selling and for speculation. In hedging, forward contracts are used to hedge the obligation to deliver or purchase a commodity at a future date, in speculating if there is no liquid futures market, to be able to the rise or fall commodity prices, they are used.

In the forward agreement, the counterparties have no optionality whether or not to use the contract. That is why, at the maturity date, the buyer of a contract (holder of the long position) makes a profit or loss depending on the commodity marked to market prices. If the commodity price increases, the long position holder of forward contracts makes profit and if the commodity price falls, the buyer makes a loss.

2.7.2 Swaps

Commodity swaps are mid and long term risk management instruments used to fix the price of commodity over a specific time period. Most swaps are traded in OTC markets and financially settled and they have a commodity index. In swap, one counterparty pays the fixed price whereas the other counterparty pays the variable price given by commodity index in a number of fixing dates (Figure 2.7). In practical view, cash flow does not over regarding nominal amount, only net amounts are paid between counterparties. If the fixed price exceeds the variable price, the payer pays the difference; if the variable price is higher, the payer receives the difference (Kaminski, 2004).

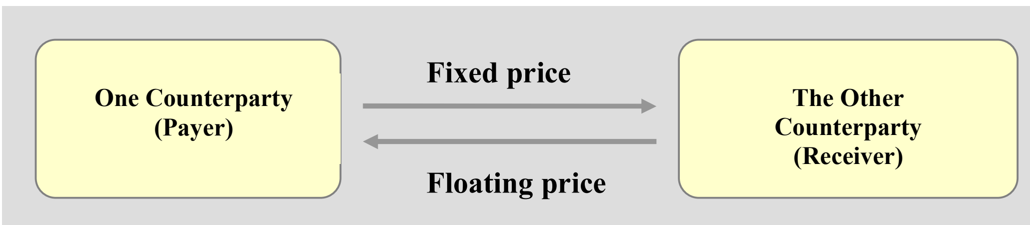

Figure 2.7 : Commodity swap.

2.7.3 Options

Option is a derivative financial instrument that establishes a contract between two parties concerning the buying or selling of a commodity at a reference price. The buyer of the option takes the right, but not the obligation, to engage in some specific transaction on the commodity, while the seller is under the obligation to fulfill the transaction if so requested by the buyer.

Options can be classified into two groups regarding the obligation; call and put option. Call option gives the right to buy the commodity and put option gives the right to sell the commodity.

In option, as like forward and futures contracts, the maturity date, contract size, the price were specified. The reference price at which the underlying can be traded is called the strike price or exercise price. The price of an option derives from the difference between the reference price and the value of the underlying commodity plus a premium based on the time remaining until the expiration of the option. The option holder has the right to use or not use the right. If the holder uses the right, the process of activating an option and thereby trading the underlying at the agreed-upon price is referred to as exercising it. Most options have an expiration date. If the option is not exercised by the expiration date, it becomes invalid (Beutel, 2005).

2.7.4 Futures contracts

Futures contracts are standardized forward contracts traded at commodity exchanges where a clearing house serves a central counterparty for all transactions (Figure 2.8). Forwards contract are OTC trades and carries credit risk of counterparties. Due to clearing house, there is no counterparty credit risk between the traders in futures contracts. The commodity exchange sets the rules to protect the clearinghouse from possible losses. One of the most important rules settled for this purpose is initial margin requirement. Trading participants have to pay an initial margin as guarantee. This initial margin amount is equal to approximately 10% of the total notional contract value. At the end of each trading day, a settlement price for the futures contract is determined and gains and losses should be realized at a margin account.

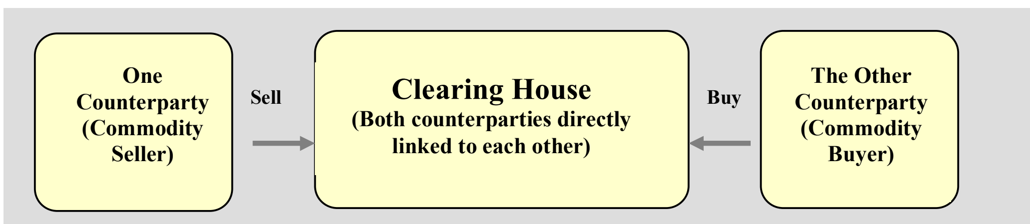

Figure 2.8 : Commodity futures contract.

Futures contracts are more favorable than forward contracts for speculators because they often do not lead to physical delivery and they are settled financially. Because of futures contracts being standardized and traded against a central counterparty, it is easy to close out a futures position by executing a trade opposite to the first one so at the maturity, the obligator not to have to delivery or buy the commodity.

Futures contract commits one party to sell and the other party to buy a stipulated quantity and grade of commodity at a settled price on or before a given date in the future. It requires the daily settlement of all gains and losses until the maturity date if the contract is not close. Moreover, it provides the delivery of commodity if it is required; otherwise final cash payment settlement is needed to close the position.

Key features of futures contracts;

- The buyer of a futures contract called as long position, accepting to receive the delivery
- The seller of a futures contract called as short position, accepting to make the delivery.
- The contracts are traded on regulated exchanges either by open outcry in specified trading areas or electronically.
- Futures contract are marked to market daily at the end of day settlement prices.
- Futures contracts can be closed by an offsetting transaction at any time prior to the expiry of the contract.

The standardized energy futures contract specifies:

- Underlying instrument: The energy commodity the contract based
- Size: The amount of contract (1 contract=100 mtons)
- Delivery cycle: The specified months at which contracts traded such as 1 month, 2 month
- Expiry date: The date on which the delivery or offsetting the position will terminate
- Grade or quality specs: The quality is specified in detail and the delivered product quality gets premium or discount compared with the quality in contract.

The long position holder can get profit if the commodity prices go up and vice versa. These profits and losses are paid daily via the variation futures margin. The broker at the clearing house finances the customer or calls the customer for collateral against unrealized losses.

Table 2.7 : International energy markets (Source: Dahl, C.A. (2004), International Energy Market: Understanding Pricing, Policies and Profits).

Product	**Traded Since**	**Delivery**	**Exchange, Location**	**Web Page, http://**
Brent Crude	6/88	Sullom Voe	ICE,UK	www.ice.com
Gasoil	4/81	ARA	ICE,UK	www.ice.com
Crude Oil,Light Sweet	6/02	No Delivery	Merchant Exchange, U.S.	www.merchants-exchange.net/
Crude Oil, Brent	6/02	No Delivery	Merchant Exchange, U.S.	www.merchants-exchange.net/
Gasoil, European Gasoline Unleaded	1/02 6/02	No delivery No Delivery	Merchants Exchange, U.S.	www.merchants-exchange.net/
Heating Oil	1/02	No Delivery	Merchants Exchange, U.S.	www.merchants-exchange.net/
Gasoline, Unleaded	12/84	NHY	NYMEX,U.S.	www.nymex.com
Heating Oil	10/74	NHY	NYMEX,U.S.	www.nymex.com
Crude Oil, Light Sweet	3/83	Cushing, Oklahoma	NYMEX, U.S.	www.nymex.com
Crude Oil, Brent	4/01	No Delivery	NYMEX,U.S.	www.nymex.com
Crude Oil, Lt Sweet, EminNY	6/02	No Delivery	NYMEX,U.S.	www.nymex.com
Gasoline	7/99	Tokyo, Kanagama, Chiba	TOGOM, Japan	www.tocom.or.jp/
Middle Eastern Crude	9/01	No Delivery	TOGOM, Japan	www.tocom.or.jp/
Heating Oil	04/02	No Delivery	Hannover Commodity Exchange, Germany	www.wtb-hannover.de/

ARA: Amsterdam, Rotterdam, Antwerp., EEX:European Energy Exchange., EminNY: Smaller contracts traded on the Chicago Mercantile Exchange electronic system (Globex) but cleared on NYMEX, ICE: Intercontinental Exchange., NBP:Transco's National Balancing Point on U.K.Grid., NYMEX:New York Mercantile Exchange, NSW:New South Wales, Australia, NHY: New York Harbor, TOCAM: Tokyo Commodity Exchange

An estimated 80% of the world's energy futures ad options are in NYMEX (Table 2.7). Trading is done by open outcry in the trading pit and by electronic trading after hours on its access began in June 1993. In the Figure.2.9, the oil futures market is shown.

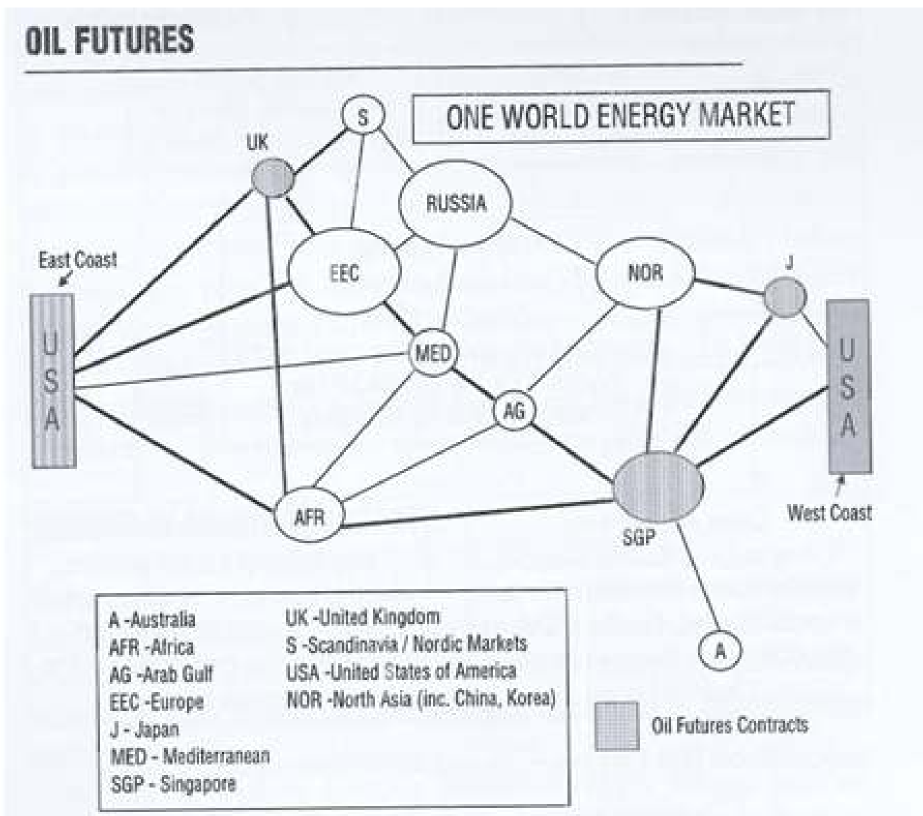

Figure 2.9 : Energy markets: Price Risk Management and Trading, James (2008).

2.8 Thesis Subject

In the volatile energy market, how the energy company can survive is an attractive issue for researchers. In the last decade, many energy companies went bankruptcies and their failure reasons have been discussed and analyzed in detail. Many professions and researchers agreed on the reasons of these failures as the lack of risk management.

In the thesis, the contribution of market risk management process into an energy company has been investigated. The company is an energy company owning refinery unit. Due to either legal obligation or the continuity of business, energy firms should stock the commodities so the Company has to be exposed to price risk due to carrying physical stock and volatile oil prices. The hypothesis is that could an energy company enhance its firm value by market risk management techniques?

2.8.1 Company's characteristics

The portfolio of energy company consists of five major energy commodities; gasoil, gasoline, fuel oil, jet and crude oil due to having refinery unit. Figure 2.10, shows the high volatility of product return. Time interval for keeping stock is considered as one month regarding the company's stock turnover rate, required time for supply process and accounting time period.

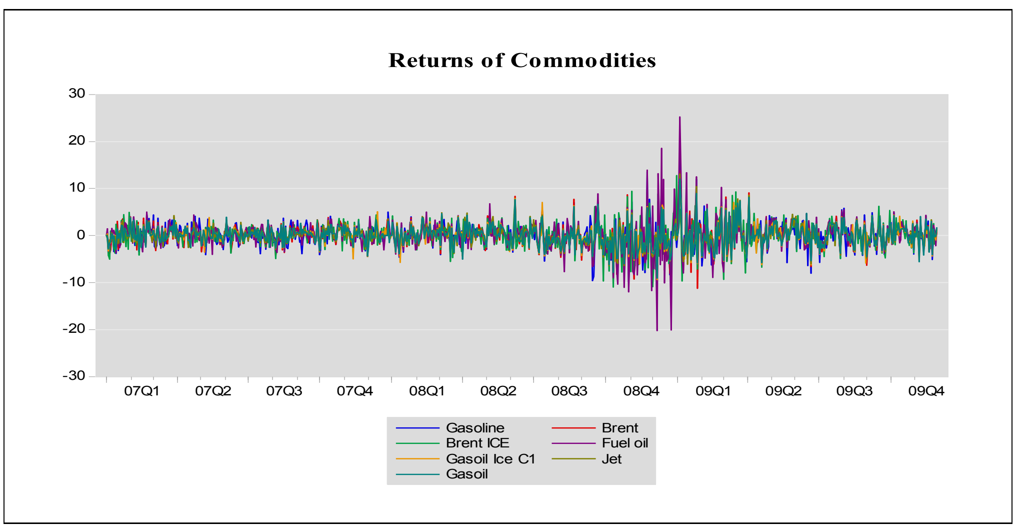

Figure 2.10 : Volatility of commodities (Platts, Url-13).

In the thesis, at what level the company should hedge its physical stock by chosen underlying futures contracts to mitigate price risk is the main issue. The level is called as optimal hedge ratio. Optimal hedge ratio analysis has been done by regarding minimum Value at Risk (VaR) of the portfolio. Value at Risk is one of the most popular risk measurement techniques in the last decades. It firstly was used in financial market and then now commonly used in also energy markets. There are three different methodologies to measure VaR; parametric, historical and monte carlo methods. In historical methodology, VaR directly depends on historical data. Parametric methodology (variance-covariance methodology) is based on volatility of portfolio. Principal component analysis (PCA) has been used to shrinkage the var-cov matrix which is used in parametric methodology before multivariate generalized autoregressive conditional heteroskedasticity (GARCH) analysis. After MGARCH analysis of generated PCAs, the var-cov matrix of the portfolio has been obtained and minimum VaR analysis in parametric method has been completed. In monte carlo methods, the random variables have been generated regarding the distribution of the time series. The hedge efficiencies of three models will be compared with each other and the best fit model result will be challenged with non-hedged portfolio P/L.

2.8.2 The Company's portfolio breakdown

The portfolio consists of five major energy commodities: gasoil, gasoline, fuel oil, jet and crude oil. The hedging instruments are Brent and gasoil ICE futures contracts. As of 30 Nov 2009;

Table 2.8 : Portfolio breakdown.

Portfolio Breakdown	Physical Stock (tons)	Prices (USD)	Portfolio Value (USD)
Gasoil	40.000	624	24.950.000
Gasoline	10.000	701	7.007.500
Fuel oil	10.000	449	4.490.000
Jet	10.000	656	6.560.000
Brent Crude Oil	30.000	571	17.122.335
Total Physical Stock	**100.000**		**60.129.835**
Ice Gasoil	70.000	614	42.997.500
Ice Brent	30.000	585	17.538.045
Ice Total	**100.000**		**60.535.545**

2.8.3 Commodity prices

In this study, daily spot prices relative to five major energy commodities: Platts[7] Gasoil, Platts Gasoline, Platts Fuel oil, Platts Jet, Brent crude oil and futures prices relative to two energy futures contracts: ICE Gasoil Futures and ICE crude oil are used. The sample covers the period from January 2007 to November 2009, resulting in 761 daily observations. The price movements of commodities in physical portfolio are shown in Figure 2.11-Figure 2.15.

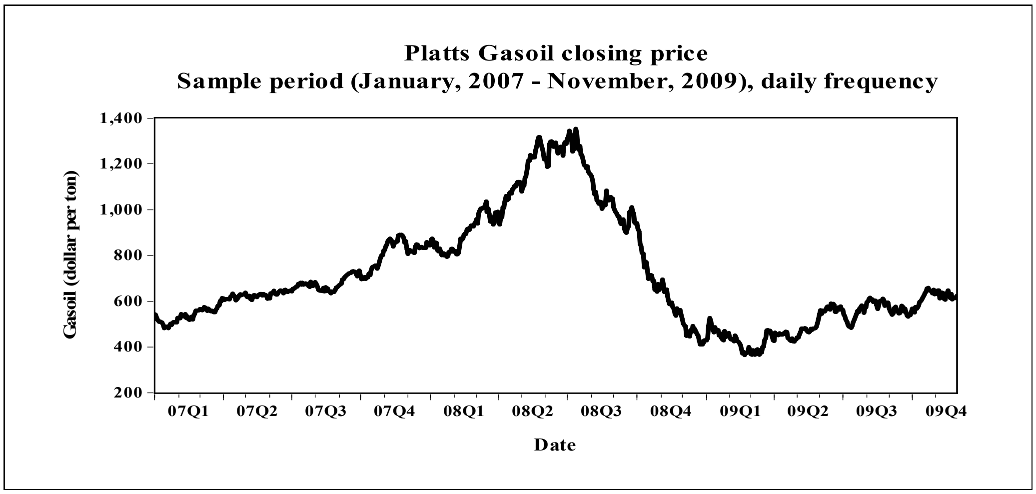

Figure 2.11 : Platts Gasoil closing price.

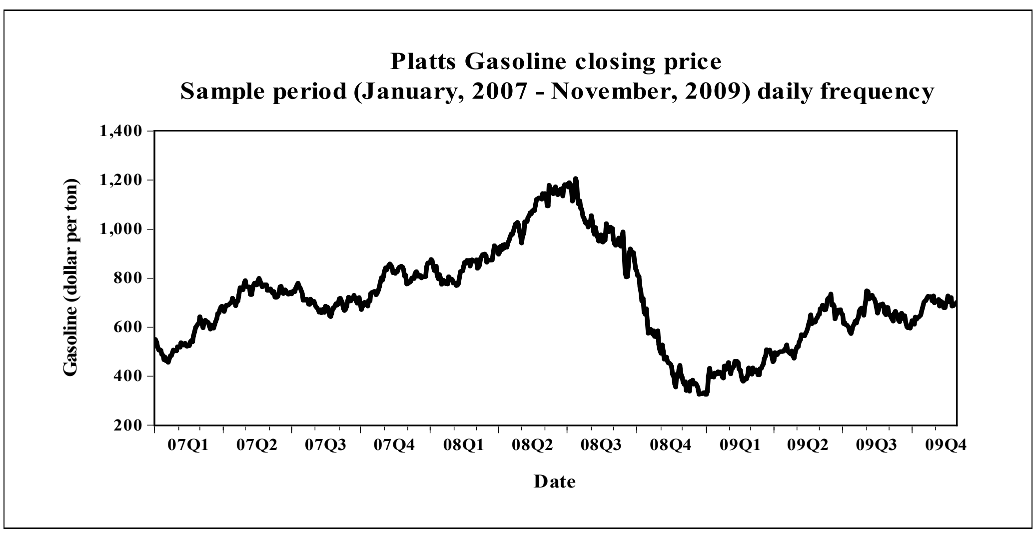

Figure 2.12 : Platts Gasoline closing price.

[7] Platts: Platts is the leading global provider of energy and metals information and the world's foremost source of benchmark price assessments in the physical energy markets since 1909.

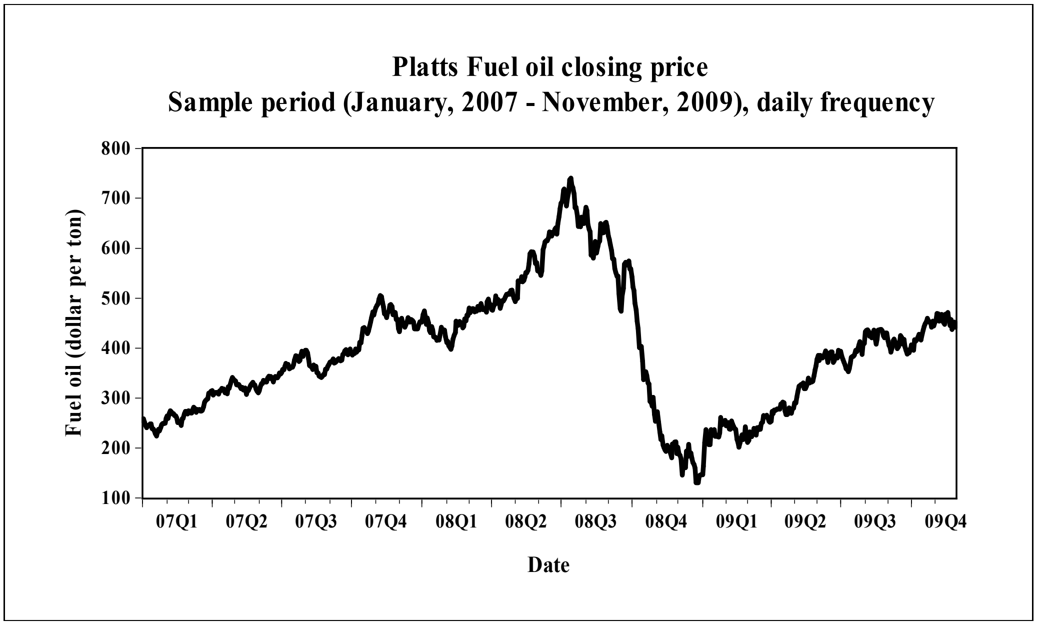

Figure 2.13 : Platts Fuel Oil closing price.

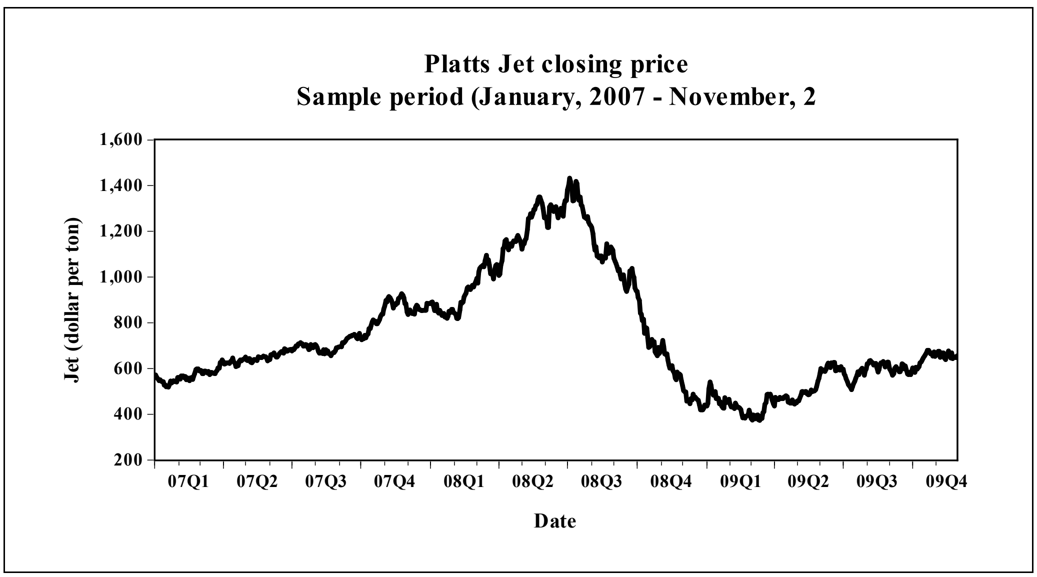

Figure 2.14 : Platts Jet closing price.

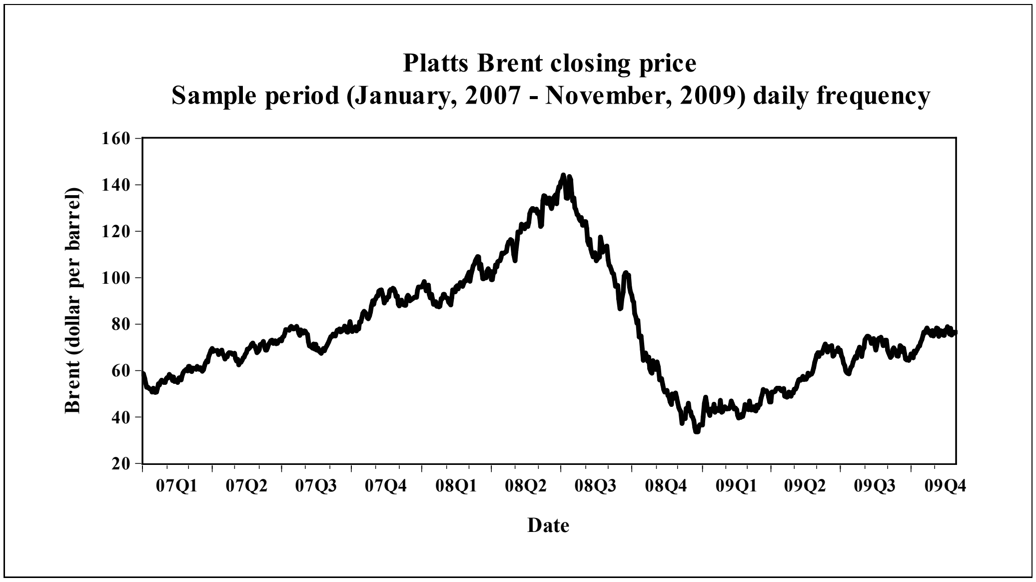

Figure 2.15 : Platts Brent closing price.

The price movements of hedging commodities; ICE Brent futures and ICE gasoil futures are shown in Figure 2.16-Figure 2.17.

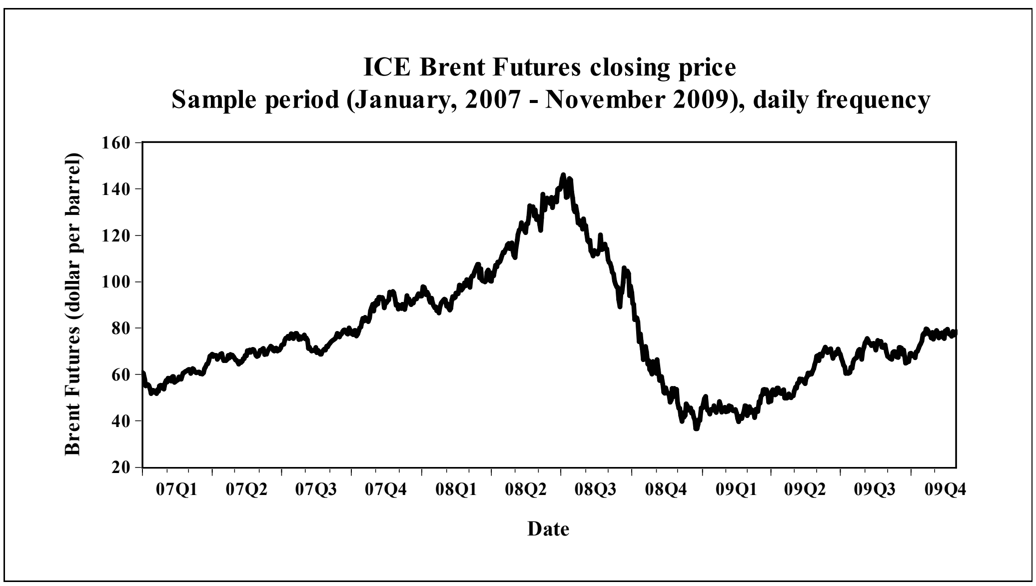

Figure 2.16 : ICE Brent Futures closing price.

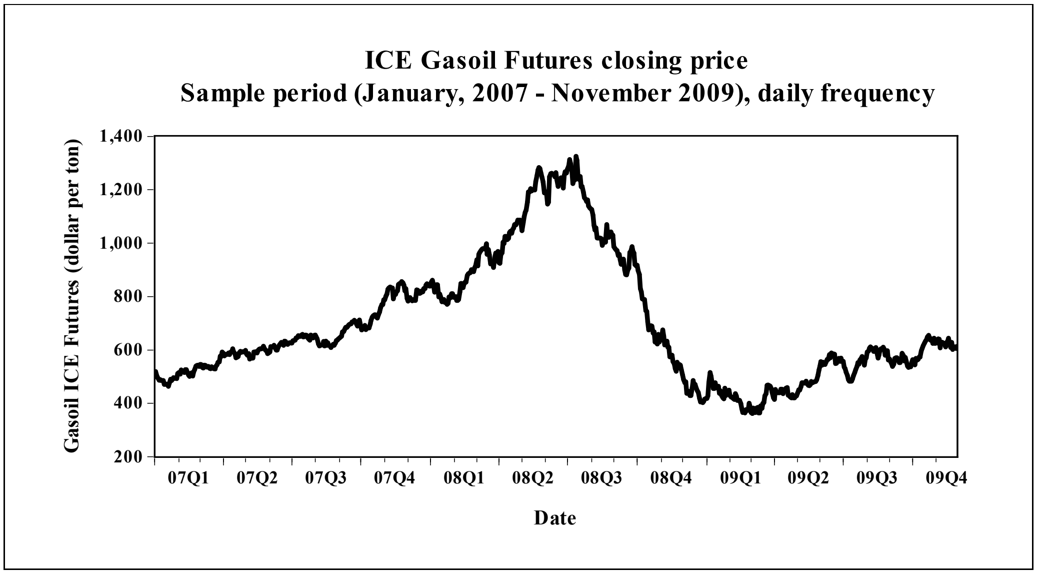

Figure 2.17 : ICE Gasoil Futures closing price.

2.8.4 Specifications of futures contracts used in the this study

2.8.4.1 ICE Brent crude futures contract

Date of launch

23 June 1988 – Only money settlement, no physical delivery

Trading hours

Local time, electronic 08:00-09.45

Local time, open outcry 10:02-19:30

Specifications

Brent blend supplied at Sullom Voe

Quotation

Priced in U.S. dollars and cents per barrel

Unit of trading

1 contract: 1.000 net barrels of Brent crude oil

Minimum price fluctuation

One cent barrel, equivalent to a tick value of USD 10

Maximum price fluctuation

Unlimited

Daily margin

Market to market daily

Trading period

12 consecutive months, quarterly out to a max 24 months and 0.5 year out to a max 36 months

Position limits

Unlimited

2.8.4.2 ICE Gasoil futures contract

Date of launch

6 April 1981 –physical delivery

Trading hours

Local time, electronic 08:00-09.00

Local time, open outcry 09:15-17:27

Specifications

In bulk and free of all liens and claims.

Quotation

Priced in U.S. dollars and cents per ton.

Unit of trading

1 contract: 1.00 metric tons of gasoil

Minimum price fluctuation

25 cents per ton, equivalent to a tick value of USD 25.

Maximum price fluctuation

Unlimited

Daily margin

Market to market daily

Trading period

12 consecutive months, quarterly out to a max 24 months and 0.5 year out to a max 36 months

Position limits

Unlimited

3. VALUE AT RISK

3.1 VaR in Energy Markets

Competition and deregulation in energy markets has led to relatively free energy markets in which fluctuations in oil prices are very high. To be able to mitigate, oil price risk within oil markets after OPEC agreements in the 1970s requires risk quantification. Value at risk is an essential tool at risk quantification even for volatile oil prices. Mauro (1999), Badeshi, Shavvalpour, (2005), Hamidieh (2008) and Casassus (2004) used VaR to evaluate the risk of oil prices. Chaker and Mabrouk (2010) used VaR for some major crude oil and gas commodities for both short and long trading positions. They computed the VaR for three ARCH/GARCH-type models. Cabedoa and Moyab (2003) provide estimation for the maximum oil price change associated with a likelihood level, and used for designing risk management strategies. They analyze three VaR calculation methods: the historical simulation standard approach, the historical simulation with ARMA forecasts (HSAF) approach, developed in this paper, and the variance–covariance method based on autoregressive conditional heteroskedasticity models forecasts.

Zheng (2006), Butler (1999) also used VaR in their financial risk measurements by modeling volatility. Jalali-Naini and Manesh (2006), Terry (2005) and Hung, Lee, Liu (2007) studied VaR in their risk quantifications in determination of optimal hedge ratio.

3.2 The History of VaR

The origin and developments of risk management started work in financial institutions. Due to high volatility in financial markets, financial institutions started development in internal models to measure and aggregate risks across the institution since the late of 1970s. Before regulatory authorities obligation about risk management, they started work on their internal models in the first instance for their own risk management purposes to be able to aggregate their risks taking account of how they interact with each other and they developed their own models.

The best known and common model belongs to JP Morgan. RiskMetrics is the system to give a daily one page report indicating risk and potential losses over the next 24 hours to the Chairman of JP Morgan, Dennis Weatherstone. The Morgan had to develop a system to measure risks across different trading positions, across the whole institution, and also aggregate these risks into a single risk measure, called Value at Risk (VaR). The new risk system was highlighted in JP Morgan's 1993 research conference and aroused a great deal of interest from potential clients who wishes to buy or lease it for their own purposes.

JP Morgan decided to make its data and basic methodology available so that outside parties could use them to write their own risk management software. Early in 1994, Morgan set up the RiskMetrics unit to do this and the RiskMetrics model-a simplified version of the firm's own internal model- was completed in eight months. RiskMetrics system was freely available on the internet in October 1994. Making its data available gave a major boost to the spread of VaR systems by giving software providers and their clients access to data sets that they were often unable to construct themselves. Among first securities houses, investment banks, and then commercial banks, pension funds, other financial institutions and non-financial corporate, VaR system was adopted rapidly. Development with IT and software industry, VaR system were extended to cover more types of instruments and more types of risks including credit risks, liquidity risks and cash-flow risks.

VaR provides a common consistent measure of risk across different positions and risk factors. Moreover, it takes account of correlations between different factors. If two risks offset each other, the VaR allows for this offset and tells that the overall risk is fairly low. If the same two risks don't offset each other, the VaR takes this into account as well and gives a higher risk estimate. Risk measure accounting for correlations is essential if statistically meaningful way in portfolio risk measurement is required.

VaR can be used in many ways; determination of risk appetite, risk tolerance, capital allocation, reporting and disclosing, investment decision, hedging and trading decision.

All these benefits of VaR, it has some drawbacks. Model risk is one of the important drawbacks and the good example is Long Term Capital Management (LTCM). In the summer and autumn of 1998, LTCM lost the amount of value that was 14 times the standard deviation of its P/L and a 14 sigma event shouldn't occur once in the entire history of the universe. Moreover, different VaR models give different VaR estimates. To prevent this undesirable result, the correct model should be chosen and implemented accurately.

3.3 Value At Risk

"Value at Risk is a measure of maximum potential change in value of a portfolio of financial instruments over a pre-set horizon. VaR answers the question: how much can I lose with x % probability over a given horizon."—J.P.Morgan's 1996 Risk Metrics Technical Document.

"Value at Risk is a measure of a point in the distribution of possible outcomes. It has two parameters: a horizon and a probability. For example, a common regulatory definition of VaR is the amount of capital that you should expect to lose no more than once in a hundred two-week intervals, given your current positions. At Goldman Sachs, we commonly focus on an amount of capital that we should expect to lose no more than once per year in a given day. We think of this not as a "worst case", but rather as a regularly occurring event with which we should be comfortable."—A 1996 Goldman Sachs research report

Value at Risk is a popular measurement technique to provide a single number summarizing the total risk in a portfolio of financial assets (Zucchini, Neumann, 1999 and Berkelaar, 2002). It has been widely used by fund managers, corporate treasurer, and corporate risk managers as well as by financial institutions.

VaR is a function of two parameters: target horizon (time horizon) and the confidence level. For a given portfolio, probability and time horizon, VaR is defined as a threshold value such that the probability that the mark-to-market loss on the portfolio over the given time horizon exceeds this value (assuming normal markets and no trading in the portfolio) in the given probability level (Jorion, 2000; Dowd, 2002; Stulz, 2003; Hull 2003; Alexander, 2001 and Harris and Sollis, 2003; Rogachev, 2002).

3.3.1 Time horizon or the holding period:

In calculating a bank's capital for market risk, holding period is taken as 10 days. This means that they focus on the loss level over a 10-day period. Holding period can change regarding the sector and underlying time series' characteristics. For financial markets, liquidity is the main issue in this decision. On the other hand, in energy risk management, the stock turnover rate and legal obligations are important decision making criteria.

$$NdayVaR = 1dayVaRx(N)^{1/2} \tag{3.1}$$

This formula is used when the changes in the value of the portfolio on successive days have independent identical normal distributions with mean zero.

3.3.2 Confidence Interval:

In calculating a bank's capital for market risk, confidence level is taken as 99%. This means the loss is expected to be exceeded only 1% of the time. The most popular confidence levels are 99% and 95%.

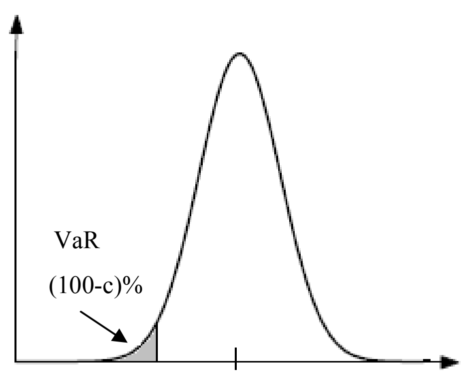

Figure 3.1 : VaR.

VaR is the loss corresponding to the (100-c)th percentile of the distribution of the change in the value of the portfolio over the time horizon (Figure 3.1). If c=95, it is the fifth percentile of the distribution of changes in the value of the portfolio over the next time horizon. Figure.3.1 shows VaR for the case where the time series (the portfolio value change) is approximately normally distributed.

VaR can be extracted from the loss from adverse market movements over a fixed time horizon under assumption of constant portfolio. VaR is the point at the lower percentile of a distribution for theoretical profit and loss arising from that adverse movement.

The VaR measurement summarizes the distribution of possible losses by a quantile, a point with a specified probability of greater losses. Common alternative metrics are standard deviation, mean absolute deviation, expected shortfall and downside risk.

In mathematical view, VaR can be explained by the probability distribution of the future portfolio value f(k) regarding P/L or return distribution. At a given confidence level (c), the worst possible realization K* such that the probability of exceeding this value is c (Jorion, 2001):

$$c = \int_{K^*}^{\infty} f(k)dk \tag{3.2}$$

or the probability of a value lower than K*, p=P(k≤K*), is 1-c:

$$1-c = \int_{-\infty}^{K^*} f(k)dk = P(k \leq K^*) = p \tag{3.3}$$

If the confidence level is 95%, the area from -∞ to K* sum to p=1-c, 5%.

Computation of VaR;

- Mark-to-market of the current portfolio
- Calculate the volatility of risk factors
- Set of time horizon (1 day, 10 days or 1 month)
- Set of confidence level (99%, 95%)
- Calculate the VaR at settled confidence level

3.4 VaR Methodologies

3.4.1 Historical Simulation

Historical simulation is the simplest way of simulating VaR because it is a theoretical approach that does not require any assumption about the statistical probability distributions of data. It uses the past data in a very direct way as a guide to estimate what happen in the future. It repeatedly values current portfolio based on the market conditions that existed over a specific historical period of time. The price of the current portfolio can be taken as deterministic function of market parameter P(x). P is the pricing function and x is the vector of all relevant market parameters. Today's price is $P(x_t)$. The market parameters at some day k were x_k and on day k+1 the parameter was x_{k+1}. The possible changes in today's parameters can be modeled and the tomorrow price is $P(x+ (x_{k+1}-x_k)$. After calculation of profits and loss for each h-day period, by ordering the resulting data, the VaR value at required quantile (5%, 10%) of worst outcomes (5% quantile means 95 % confidence interval). More generally, it involves using historical percentage changes in underlying prices and prices to construct a distribution of potential future profits and losses, and then taking the value at risk as the loss that is exceeded only x % of the time. In summary, it is the simplest method involving the current portfolio across a set of historical price changes to yield a distribution of changes in portfolio value and computing a percentile.

It requires full valuation. It means that it consists of going back in time with current portfolio to a time series of historical asset returns. The actual distribution for the data is being used so it does not depend on any assumption, especially normality assumption. This method considers fat tails and it is independent of model risk. The estimated VaR depends on historical values.

In full valuation, the methodology consists of going back in time and applying current weights to a time series of historical asset return:

$$R_{opak}=\sum_{i=1}^{N} w_{i,t} R_{i,k} \qquad \textbf{(3.4)}$$

k=1, 2, t. & w_t: the weights at their current values.

3.4.1.1 Computation of VaR of the portfolio

In summary, the historical method graphs the actual daily returns over a user-specified past period into a histogram. For a two-year observation period (500 trading days) the 1% VaR would be the loss on the fifth-worst day, and the 5% VaR would be the loss on the 25th-worst day.

Single instrument portfolio

- The first step is to identify the market variables affecting the portfolio if the portfolio consists of more than one variable.
- The next step is to get a formula expressing the mark-to-market value of the current portfolio (logarithmic returns).
- Obtain historical values of the market factors for the last N periods. The data set should be determined. Generally, two year daily data is taken.
- Take the current portfolio to the changes in market rates and prices experienced on each of the most recent approximately 500 business days (two year data).
- Calculate the daily profit and losses of the current portfolio which is mark-to-marked.
- Order the mark-to-market profits and losses descending or graph the actual daily returns over a defined period into a histogram.
- Get the loss which is equaled or exceeded at confidence level (95% or 99%).

Multiple instruments portfolios

The extension of above methodology is aggregation of all mark-to-market profits and losses of every instrument. The P/L of the instruments can be get together regarding their weights in the portfolio.

This approach has advantages and disadvantages. Firstly let's talk about the advantages. It is very intuitive. Different from parametric method, it does not depend on any assumption on the distribution of changes in the underlying instruments. Moreover, it is very sensitive to fat tails, it can handle them and extreme event risks and asymmetric distributions. In spite of all these advantages, it also has some drawbacks. Dependency only on historical value can be misleading. When the heavy loss data is taken off from historical time series, the VaR is directly affected from this extraction. Next calculated VaR probably will be less than the previous one due this event and the results are not stable. Moreover, the requirement for a large market database is the disadvantage.

3.4.1.2 Advantages and disadvantages of Historical Simulation

Table 3.1 : Historical simulation pros & cons.

Pros	**Cons**
It does not depend on any distribution assumption so it is applicable for all instruments.	Extreme events affect the VaR value very much if exist in data set.
Volatility and correlation estimation are not required, they are embedded in the data set.	Data set length is important. Statistically enough data should be there.
Due to being independent from any distribution dependency, fat tails of distributions and other extreme events are captured if they exist in data set.	It cannot be used in sensitivity analysis.
Aggregation across market is straightforward.	
Provides a full distribution of potential portfolio of values (not just a specific percentile)	
It is faster than Monte Carlo simulation because fewer scenarios are used to current conditions.	

3.4.2 Monte Carlo

3.4.2.1 Computation of VaR of the portfolio

Single instruments portfolios

Similar to historical simulation, the Monte Carlo steps of VaR calculation can be described as;

- The first step is to identify the market variables affecting the portfolio if the portfolio consists of more than one variable.
- The next step is to get a formula expressing the mark-to-market value of the current portfolio (P/L or logarithmic returns).

- Obtain historical values of the market factors for the last N periods. The data set should be determined. Generally, two year daily data is taken.
- Determine the distribution of time series (market risk factors series) and parameters of the distributions.
- Use random generator to generate N hypothetical values of changes in the market factors based on the selected distribution. 10,000 simulations are the preferable number to get the significant result.

Multiple instrument portfolios

- The most important critical point is to generate random values of the instruments by considering correlation matrix of the portfolio.
- The extension of above methodology is aggregation of all mark-to-market profits and losses of every instrument. The P/L or return series of the instruments can be getting together regarding their weights in the portfolio. The joint distribution of returns of series for all market factors must be determined.

3.4.2.2 Advantages and disadvantages of Monte Carlo method

Table 3.2 : Monte carlo pros & cons.

Pros	**Cons**
It does not depend on any distribution assumption so it is applicable to all instruments.	It requires high capacity computers for simulation.
Complex portfolio models can be handled.	Simulations take long time, it is time consuming.
It can be used in sensitivity analyses and stress testing.	

3.4.3 Parametric VaR

Different from historical simulation and monte carlo methodology, the most distinguishing property of parametric methodology, called also as variance-covariance method is that the distribution of the underlying instruments is assumed to belong to a parametric family, especially the normal distribution. This leads to simplification in evaluation because the VaR figure can be calculated directly from the portfolio standard deviation using a multiplicative factor that depends on the confidence level. In historical and Monte Carlo methods, VaR is getting just from reading the quantile off the empirical distribution, on the other hand, in this methodology; it depends on the estimation of parameters, especially standard deviation. That's why; this method was called as "parametric".

Let's the distribution of f(k) into a standard normal distribution $\Phi(\varepsilon)$ where ε has mean zero and standard deviation of unity. As application of normalization procedure to general distribution; let's define the value K*as K*=Ko(1+R*). R* can be negative, so the absolute value of it can be taken; -|R*| (Jorion, 2000).

R* with a standard normal deviate $\alpha > 0$; $-\alpha = \dfrac{-|R^*| - \mu}{\sigma}$ **(3.5)**

The VaR approach can be applicable for this normalized distribution as;

$$1 - c = \int_{-\infty}^{K^*} f(k)dk = \int_{-\infty}^{|R^*|} f(r)dr = \int_{-\infty}^{\alpha} \phi(\varepsilon)d\varepsilon \qquad \textbf{(3.6)}$$

The area to the left of α is equal to 1-c and it is VaR. The cumulative standard normal distribution function explains this issue. The area to the left of a standard normal variable with value equal to d is:

$$N(d) = \int_{-\infty}^{d} \phi(\varepsilon)d\varepsilon \qquad \textbf{(3.7)}$$

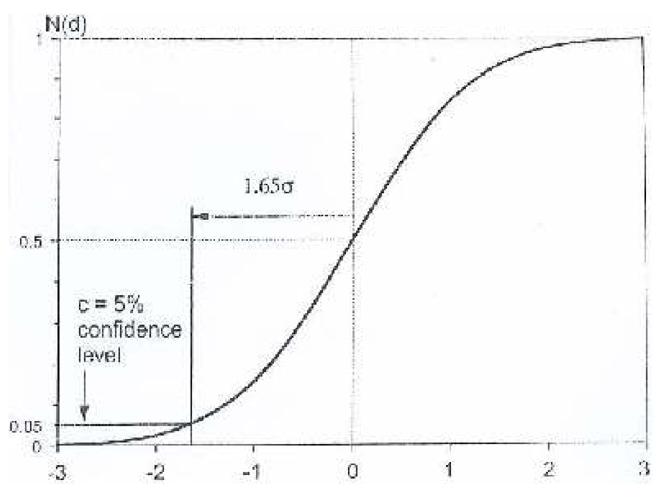

Figure 3.2 : Cumulative Normal Probability Distribution.

Figure 3.2. shows how the N(d) function goes to 1 when the standard normal variable "d" goes to +∞. At d=0, N(0)=0.5 says that the area under the curve is 50%.

In risk management view, the focus is the left tail of the distribution, generally the worst loss side (sometimes the focus can be right tail side depending on the position long or short). In Figure 3.2., 95% confidence level is shown. Here, at 95% confidence level, VaR of a standard normal variable corresponds to a value of α=1.65 below 0. R* in general formula:

$$R^* = -\alpha\sigma + \mu \quad \textbf{(3.8)}$$

Here, the parameters μ and σ are on annual basis and the time interval is considered in years.

Under uncorrelated return assumption, the time aggregation result can be formulated as:

$$VaR(mean) = -Ko(R^* - \mu) = Ko.\alpha.\sigma.\sqrt{\Delta t} \quad \textbf{(3.9)}$$

3.4.3.1 Advantages and Disadvantages of Parametric Method

Table 3.3 : Parametric prons & cons.

Pros	**Cons**
It is very simple and takes only few minutes to calculate the variance.	It depends on assumption that the return of underlying instrument is normally distributed.
The calculation of incremental VaR is easy to implement.	The estimation of volatilities of risk factors and correlations (or variance-covariance matrix) is required.
	For having more than second-order expansion risk factors such as option, the model is not sufficient.
	It cannot be used to conduct sensitivity analysis.

4. TIME SERIES MODELS

4.1 Asset Return

Similar to financial time series and VaR analysis of financial instruments, in energy risk management, most studies are done regarding return series instead of their prices. Campbell, Lo and MacKinlay (1997) suggested using return regarding two main reasons; return is a complete and scale-free summary of the instrument and it is also easer to analyze than price series

4.1.1 One-period simple return

Simple gross return of asset holding for one period from date t-1 to date t is (Tsay, 2002);

$$1 + R_t = \frac{P_t}{P_{t-1}} \text{ or } P_t = P_{t-1}(1 + R_t) \tag{4.1}$$

$$R_t = \frac{P_t}{P_{t-1}} - 1 = \frac{P_t - P_{t-1}}{P_{t-1}}$$

4.1.2 Multiperiod simple return

Simple gross return of asset holding for k periods between dates t-k and t is (Tsay, 2002)

$$1 + R_t[k] = \prod_{j=0}^{k-1}(1 + R_{t-j}) \tag{4.2}$$

4.1.3 Continuously compounded return

Continuously compounded return (log return) is the natural logarithm of the simple gross return of an asset and can be formulized as;

$$r_t = In(1 + R_t) = In\frac{P_t}{P_{t-1}} = p_t - p_{t-1} \qquad \text{where } p_t = In(P_t) \tag{4.3}$$

Advantages of continuously compounded returns instead of simple net return:

$$r_t[k] = In(1 + R_t[k]) = In[(1 + R_t)(1 + R_{t-1})...(1 + R_{t-k+1})] \quad \textbf{(4.4)}$$

$$= In(1 + R_t) + In(1 + R_{t-1}) + ... + In(1 + R_{t-k+1})$$

$$= r_t + r_{t-1} + ... + r_{t-k+1}$$

4.1.4 Portfolio return

The simple net return of a portfolio (p) at time t is $R_{p,t} = \sum_{i=1}^{N} w_i R_{it}$ where; **(4.5)**

N: The number of assets in the portfolio

w_i: the weight of the asset i in the portfolio (as percentage)

The continuously compounded return of a portfolio (p) at time t is $r_{p,t} \approx \sum_{i=1}^{N} w_i r_{it}$ where; **(4.6)**

N: The number of assets in the portfolio

w_i: the weight of the asset i in the portfolio (as percentage)

4.2 Random Variables

A random variable can be discrete or continuous. A random variable has either an associated probability distribution (discrete random variable) or probability density function (continuous random variable).

4.3 Expected Value

The expected value of a random variable x says its average value and it can be shown as E(x) or μ. It can be formulized regarding variables being discrete or continuous. If x is a continuous random variable with a probability density function f(x),

$$\mu = E(x) = \int xf(x)dx \quad \textbf{(4.7)}$$

On the other hand, if x is a discrete random variable with possible values x1,x2, x3…,xn and p(xi) and P(X=xi), $\mu = E(x) = \sum x_i \ p(x_i)$ **(4.8)**

4.3.1 Variance and standard deviation

The variance of a random variable gives an idea of how widely spread the values of the random variable. The larger the variance, the more scattered the observations on average are. Variance can be symbolized Var(x) or σ^2 .

$$Var(x) = \sigma^2 = E[x - E(x)]^2 = E(x^2) - E(x)^2 \quad \textbf{(4.9)}$$

where E(x) is the expected value of the random variable x.

Volatility is a measure of the dispersion Volatility most frequently refers to the standard deviation of the continuously compounded returns of an underlying instrument within a specific time horizon. It can be symbolized STD(x) or σ.

$$Std(x) = \sigma = \sqrt{Var(x)} = \sqrt{\sigma^2} = \sigma \quad \textbf{(4.10)}$$

4.4 Key Features of Economic Time Series

A time series "y_t" is a discrete time continuous state process in which the variable y is identified by the value and takes at time t, denoted y_t. Time trend, $y_t = t$ is a deterministic time series. White noise, a basic stochastic time series is $y_t = \varepsilon_t$ where ε_t an independent is and identically distributed (i.i.d) variable with mean 0 and variance σ^2 for all t, written $\varepsilon_t \sim$ i.i.d. $(0, \sigma^2)$.

4.4.1 Trends

Trend is a long term movement in a time series and one of the most dominant features of economic and business time series. Trend can be upward or downward, it can be steep or not and it can be exponential or linear. Trend usually can be predictable by using regression analysis. The simple regression model assumes that the trend in y_t can be shown as;

$$y_t = \alpha + \beta t + \varepsilon_t \qquad t = 1,2,....,n \qquad \textbf{(4.11)}$$

where α and β are unknown parameters and ε_t is an unknown residual error time series. An alternative method to get the trend pattern is to consider the growth rate of the variable. If the raw data are denoted by w_t, forecast $y_t = \log(w_t)$, it follows that

$$y_t - y_{t-1} = \log(w_t / w_{t-1}) = \log\left[1 + (w_t - w_{t-1}) / w_{t-1}\right] \approx (w_t - w_{t-1}) / w_{t-1} \qquad \textbf{(4.12)}$$

When $(w_t - w_{t-1}) / w_{t-1}$ is small.

Significant average growth rate is a good indicator of a trend pattern of economic time series.

$$y_t - y_{t-1} = \mu + \mu_t \qquad t = 2,3,.....,n. \qquad \textbf{(4.13)}$$

The most important feature is that trend can be get rid off by differencing the data if y_t has a stochastic trend (Franses, 1998 and Alexander, 2001).

4.4.2 Seasonality

Seasonality is very common in economic and energy time series. Seasonality can be defined as the pattern regarding periodic movements like sine and cosine movements. For example, on winter, the oil sales decline and price tend to go upward. It is easily noticeable from a simple graph of the time series. Here, the experience takes more importance because analyst should identify the cyclic by looking the graph. If the graphs are not informative, using regression with dummy variables can be helpful.

$$y_t - y_{t-1} = \mu_1 D_{1,t} + \mu_2 D_{2,t} + ... + \mu_s D_{S,t} + \mu_t \qquad t = 2,3,....,n, \qquad \textbf{(4.14)}$$

where $D_{s,t}$ is a seasonal dummy variable with

$$D_{s,t} = 1 \text{ when } t = (T-1)S + s \text{ with } s = 1,2,....,S \text{ and } \quad T = 1,2,...,N. \qquad \textbf{(4.15)}$$

$D_{s,t} = 0$ otherwise.

4.4.3 Aberrant observations

Aberrant observations can be called as outliers. They like outliers, only single observations have a major impact on time series modeling and forecasting. They are unusual and surprising values with respect to the rest of the time series analyzed.

4.4.4 Conditional Heteroskedasticity (Homoskedasticity vs. Heteroskedasticity)

If the standard deviations of terms x are constant for all time t, a univariate stochastic process x is called as homoskedastic. If not, it is called as heteroskedastic, changing by time varying. Homoskedasticity means constant variance and heteroscadasticity means changing variance. Heteroskedasticity can be classified into two groups regarding either conditional or unconditional. If unconditional standard deviation is not constant, the series has unconditional heteroskedastic. It is conditionally heteroskedastic if conditional standard deviations are not constant (Figure 4.1).

Conditional Heteroskedastic Models are;

- ARCH (Autoregressive Conditional Heteroskedasticity)
- Generalized ARCH models
- Regime-swithcing models
- Stochastic volatility models

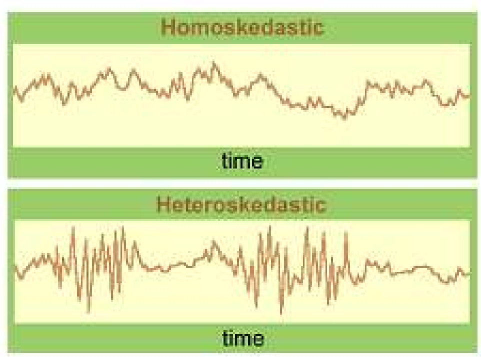

Figure 4.1: Homoskedasticity and heteroskedasticity. (Source:Riskglossary; Url-1).

4.4.5 Non-linearity

To model and estimate the parameters of non-linear time series requires more effort than linear series. The reason is that this option leads to a wide variety of possible models.

4.5 Time Series Models

4.5.1 Stationarity

Stationarity concept is very important in time series analysis and most of assumptions depend on the time series being stationary. If the statistical properties remain constant over time, a time series is said to be strictly stationary. If the mean and covariance functions are constant over time, it is said to be weakly stationary.

Time series may have stochastic and deterministic parts. Let's take

$$y_t = \alpha + \beta t + \varepsilon_t \text{ where } \varepsilon_t \sim \text{i.i.d.}(0,\sigma^2) \quad \textbf{(4.16)}$$

$E(y_t) = \alpha + \beta t$ and $V(y_t) = \sigma^2$ for all t. Moreover, the kth order auto covariance of y_t called as the unconditional covariance of y_t with y_{t-k}

$$\text{cov}(y_t, y_{t-k}) = E\left[(y_t - E(y_t))(y_{t-k} - E(y_{t-k}))\right] \quad \textbf{(4.17)}$$

$y_t = \alpha + \beta t + \varepsilon_t$ has $\text{cov}(y_t, y_{t-k}) = E\left[\varepsilon_t \varepsilon_{t-k}\right] = 0$ for all t and $s \neq 0$.

If the mean, variance and auto covariance are the same at every date t, it can be said that a time series is covariance stationary.

Weak stationary can be defined under these conditions:

$E(y_t)$ is a finite constant

$V(y_t)$ is a finite constant

$Cov(y_t, y_{t-k})$ depends only on the lag k.

For the strict stationarity, the whole joint distribution must be independent of time.

4.5.2 Correlation and autocorrelation

Correlation is a measure of co-movements between return series. Strong positive correlation means that series move together to either upward or downward. On the other hand, negative correlation implies that when one series goes to upward, other series moves to downward or vice versa.

The mathematical explanation of correlation can be simplified by covariance. Covariance is a measure of how much two variables change together. It is a simple statistical measure of co-movements between two random variables. Moreover, it is the first product movement about the mean of the joint density function.

$\operatorname{cov}(x, y) = E\lfloor (x-\mu_x)(y-\mu_y) \rfloor$ where $\mu_x = E(x)$ and $\mu_y = E(y)$

Correlation is independent of the units of measurements. For two random variables x and y, the correlation is:

$$corr(x, y) = \frac{\operatorname{cov}(x, y)}{\sqrt{\operatorname{var}(x)\operatorname{var}(y)}} \qquad \textbf{(4.18)} \qquad \rho_{x,y} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \qquad \textbf{(4.19)}$$

Due to normalization of covariance, correlation lies between -1 and +1. The closer to +1, the stronger the correlation or vice versa is. If the correlation is high (co-dependent), the series move together in the same direction. If the correlation between series is highly negative (close to -1), the series are still highly co-dependent move in opposite directions.

Autocorrelation is the specific correlation between r_t and r_{t-k}. The correlation coefficient between r_t and r_{t-k} is called the lag-k autocorrelation of r_t and denoted by ρ_k which under the weak stationarity assumption is a function of k only:

$$\rho_k = \frac{\operatorname{cov}(r_t, r_{t-k})}{\sqrt{\operatorname{var}(r_t)\operatorname{var}(r_{t-k})}} = \frac{\operatorname{cov}(r_t, r_{t-k})}{\operatorname{var}(r_t)} = \frac{\gamma_k}{\gamma_0} \text{ where } \operatorname{var}(r_t) = \operatorname{var}(r_{t-k})$$

Regarding definition, $\rho_0 = 1, \rho_k = -\rho_{-k}$ and $-1 \le \rho_k \le 1$. If a weakly stationary series rt is not serially correlated if and only if $\rho_k = 0$ for all k>0.

4.5.3 Linear Time Series models

4.5.3.1 Autoregressive (AR) models

Autoregressive model (AR) of time series means that a time series is function of its own lags. The order is important indicator. The notation AR(p) refers to the moving average model of order p. For example, if the autoregressive model of order 1, the AR(1) model can be shown as:

$$y_t = c + \alpha y_{t-1} + \varepsilon_t \text{ where } \varepsilon_t \sim \text{i.i.d. } (0,\sigma^2) \tag{4.20}$$

"c" determines the trend position upward or downward regarding being positive or negative, respectively. On the other hand, "α" determines the stability of the process. If;

$|\alpha|>1$, the time series goes to infinity ($y_t \rightarrow \pm\infty$) as t goes to infinity.

$|\alpha|=1$, the random walk model is generated,

$|\alpha|<1$, the time series is stationary.

4.5.3.2 Moving Average (MA) models

The moving average (MA) model is a common approach for modeling univariate time series models in time series analysis, The notation MA(q) refers to the moving average model of order q:

$$y_t = c + \varepsilon_t + \beta\varepsilon_{t-1} \text{ where } \varepsilon_t \sim \text{i.i.d. } (0,\sigma^2) \tag{4.21}$$

the model is a stationary representation for any values of c or β, since $E(y_t)=c$,

$$V(y_t) = (1+\beta^2)\sigma^2 \tag{4.22}$$

$$\text{cov}(y_t, y_{t-k}) = \beta\sigma^2 \text{ if k=1 and 0 otherwise} \tag{4.23}$$

That is, a moving average model is conceptually a linear regression of the current value of the series against previous (unobserved) white noise error terms or random shocks. The random shocks at each point are assumed to come from the same distribution, typically a normal distribution, with location at zero and constant scale. The distinction in this model is that these random shocks are propagated to future values of the time series.

Fitting the MA estimates is more complicated than with autoregressive models (AR models) because the error terms are not observable. This means that iterative non-linear fitting procedures need to be used in place of linear least squares. MA models also have a less obvious interpretation than AR models.

4.5.3.3 Autoregressive-Moving Average (ARMA) models

In the autoregressive moving average process of order (p,q) each observation y_t is generated by a weighted average of past observations going back p periods, together with a weighted average of random disturbances going back q periods. This process is denoted as ARMA(p,q):

$$y_t = c + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \ldots + \beta_q \varepsilon_{t-q}, \qquad \textbf{(4.24)}$$

where $\varepsilon_t \sim$ i.i.d. $(0,\sigma^2)$.

If the roots of $1 - \alpha_1 x - \alpha_2 x^2 - \ldots - \alpha_p x^p$ lie outside the unit circle, it is always invertible into an MA(∞) but is only stationary. It is invertible into an AR(∞) model if the roots $1 - \beta_1 x - \beta_2 x^2 - \ldots - \beta_q x^q$ lie outside the unit circle.

4.5.3.4 Integrated ARMA (ARIMA) models

The time series must be stationary if they are modeled by AR, MA and ARMA. Taking difference of time series is the most effective way to make them stationary. Box and Jenkins suggest differencing method to get stationary series. The most important factor is the degree of differencing, which is the number of times the data transformation is repeated. Differencing should be continued until the stationary time series is gotten.

What does ARIMA(p,d,q) imply? As mentioned above, the level at which the stationary series gotten is very important. “d” refers to degree of differencing and ARMA (p,q) is mentioned above section.

4.5.4 Non-Linear Time Series models

4.5.4.1 Conditional Heteroskedastic models

Unfortunately the returns in many financial markets are not well modeled by an independent and identically distributed process assumed in the moving average models. Autocorrelation especially in high frequency returns shows the dependencies of returns. Lower-frequency returns may not be autocorrelated, but squared returns shows the strong autocorrelation, which means returns are not independent from each other.

Positive autocorrelation in squared returns is a good indicator of volatility clustering in financial market data. This situation is known as autoregressive conditional heteroscedasticity. In 1963, Benoit Mandlebrot observed that financial returns time series exhibit periods of volatility interspersed. Autoregressive conditional heteroscedasticity (ARCH) models of volatility and correlation were first introduced by Rob Engle in 1982. It is more appropriate to use a generalization of ARCH model for financial data, the symmetric generalized autoregressive conditional heteroscedasticity (GARCH) introduced by Bollerslev in 1986.

4.5.4.2 ARCH

Autoregressive Conditional Heteroscedasticity (ARCH) model is the first volatility modeling, which brings systematic framework by Engle in 1982. This model depends on two main ideas: the mean corrected asset return is serially uncorrelated but depended and its dependence can be shown by a simple quadratic function of its lagged values.

Under assumption that today's conditional variance is a weighted average of past squared unexpected returns:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 \qquad \textbf{(4.25)}$$

$$\alpha_0 > 0,\ \alpha_1, \ldots, \alpha_p \geq 0 \qquad \varepsilon_t \mid I_t \sim N(0, \sigma_t^2)$$

The effect of a major market movement in history can be seen as increase in today's conditional variance because all parameters are constrained to be non-negative and α_0 is constrained to be definitely positive. The movement either positive or negative makes no difference in the equation due to the square operator.

4.5.4.3 Symmetric GARCH

Arch model is not popular in financial time series because of constraint in negative returns. Even simple Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is better than Arch in performance. In addition to Arch, GARCH says that the conditional variance is also affected from past volatility.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_q \sigma_{t-q}^2 \qquad \textbf{(4.26)}$$

$$\alpha_0 > 0,\ \alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_q \geq 0$$

Let's look at the special case: GARCH(1,1) comes from one lagged error square and one autoregressive term. ω is the constant term of the model, α is the GARCH error term coefficient and β is the lag coefficient and the GARCH(1,1) is:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad \textbf{(4.27)}$$

$\omega > 0$, α, $\beta \geq 0$

GARCH(1,1) model is the form of an infinite ARCH model with exponentially declining weights:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad \textbf{(4.28)}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta(\omega + \alpha\varepsilon_{t-2}^2 + \beta(\omega + \alpha\varepsilon_{t-3}^2 + \beta(...)))$$

$$\sigma_t^2 = \omega/(1-\beta) + \alpha(\varepsilon_{t-1}^2 + \beta\varepsilon_{t-2}^2 + \beta\varepsilon_{t-3}^2 + ...)$$

The value of parameters of GARCH, α and β, has a very important place in determination of the short-run dynamics of the series. Persistency of volatility is determined by β. If β is large, it means that shocks to the conditional variance of time series take a long time to terminate. If α, GARCH error coefficient, is large, the volatility moves together with market fluctuations. If α is high and β is low, volatility behaves more sensitively.

GARCH is very popular in not only financial time series but also commodity derivative time series. Especially in VaR analysis done by variance-covariance method, the modeling of var-cov matrix, GARCH modeling is the most common technique (Sadeghi, Shavvalpour, 2005) Chaker and Mabrouk (2010) computed the VaR for three ARCH/GARCH-type models including FIGARCH, FIAPARCH and HYGARCH.

Jalali-Naini and Manesh (2006), Terry (2005) and Hung, Lee, Liu (2007) used GARCH to model the series' volatilities in order to get optimal hedge ratio by using VaR. Moreover, Cleslow, Strickland (2000), Krehbiel, Adkins (2003), Humphreys (1997) used GARCH in their volatility estimation in energy commodities.

5. APPLICATION

5.1 Introduction

The physical stock portfolio of Energy Company consists of five major energy commodities; gasoil, gasoline, fuel oil, jet and crude oil due to having refinery unit. Due to high volatility in the returns of products, the Company is exposed to price risk coming from the potential of price decrease. To mitigate the price risk, the portfolio is diversified by ICE gasoil and crude oil futures contracts.

The decision of optimal hedge ratio is the main concern. In the thesis, optimal hedge ratio is determined by using minimum VaR portfolio approach. VaR figures of the portfolio for each incremental increase of 5% hedge futures contracts regarding stock amount of the physical stocks by three different methods are obtained. These studies have been applied to 30 different days at 99 and 95 confidence level.

The VaR analysis of the portfolio is executed by three methods; historical, parametric and monte carlo. For the parametric (variance covariance analysis) method, the standard deviation of the portfolio should be determined. To be able to calculate the standard deviation of the portfolio, the variance covariance matrix should be modeled in terms of mean and volatility modeling. The time series modeling of 28 elements of var-cov matrix is very time consuming and tedious. By using Principal Component Analysis, the number of elements which has to be modeled regarding mean and volatility equations is decreased to seven principal components. Next step is to GARCH modeling of principal components and then the transition of the commodity volatilities. After getting var-cov matrix of the portfolio, the standard deviation of the portfolio is gotten and VaR is obtained.

5.2 Data

Physical stocks consist of five major commodity; gasoil, gasoline, fuel oil, jet and crude oil. Daily spot prices relative to five major energy commodities: Platts Gasoil, Platts Gasoline, Platts Fuel oil, Platts Jet, Brent crude oil. Futures portfolio consists of two energy futures contracts; ICE Gasoil Futures and ICE crude oil.

The sample covers the period from January 2007 to November 2009, resulting in 761 daily observations for time series modeling. For VaR calculation in all methods, observation period is two years (500 trading days).

Confidence levels are 99% and 95 % for randomly chosen 30 days.

The modeling for return data and price data in financial and energy markets is different. Daily return series on financial and energy markets are generated by stationary process. The continuously compounded daily returns are computed as follows:

$$r_t = 100 \ln \frac{P_t}{P_{t-1}} \tag{5.1}$$

where r_t and P_t are the return in percent and the energy commodity closing price on day (t), respectively.

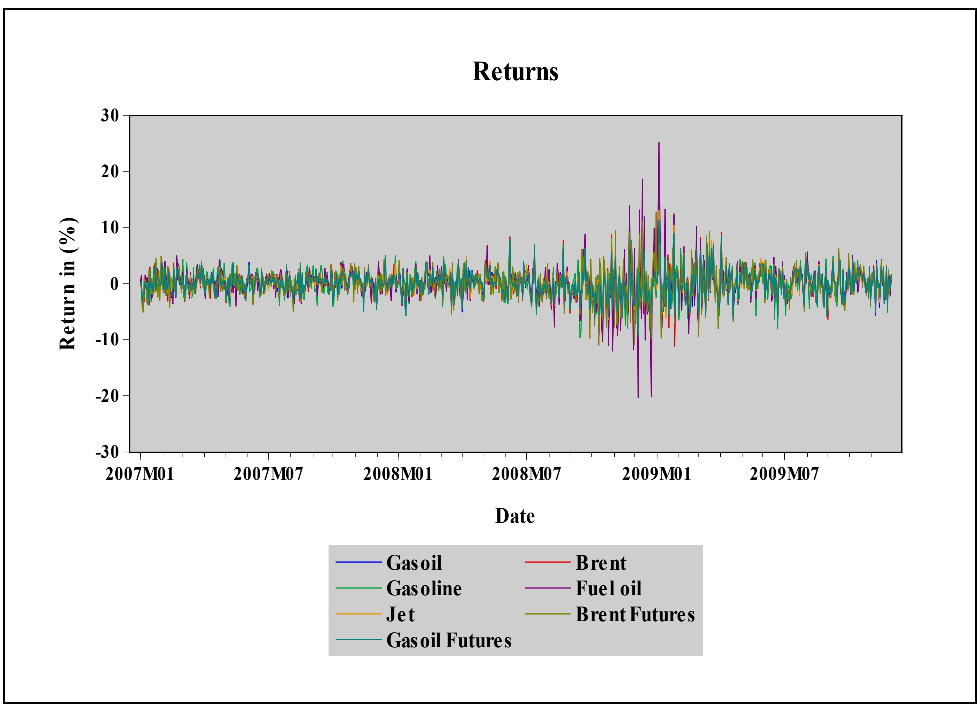

Figure 5.1 : Daily returns of portfolio.

Logarithmic returns (Figure 5.1) are used in VaR analysis because logarithmic return has more meaningful than arithmetic return. If logarithmic returns are distributed normally, then the distribution can never go to a negative value as like as price in real life. In this study, the logarithmic returns of commodities have been used. One more important reason of using logarithmic return instead of arithmetic return is that they easily allow extensions into multiple periods.

In Appendix A, the graphs of commodities' return and returns distribution have been shown separately for each commodity; from Figure A.1 to Figure A.14.

5.3 Descriptive Statistics

Table 5.1 : Descriptive statistics.

	BRENT	GASOIL	GASOLINE	FUEL_OIL	JET	ICE_BRENT	ICE_GASOIL
Mean	0.034489	0.018158	0.032670	0.074344	0.018063	0.033396	0.022776
Median	0.031164	0.000000	0.000000	0.050543	0.000000	0.096512	0.000000
Maximum	13.76749	11.94968	16.44829	25.19917	13.06658	12.70660	11.26396
Minimum	-12.76989	-9.053545	-9.889751	-20.23816	-8.856268	-10.94552	-9.437361
Std. Dev.	2.673731	2.257257	2.734898	3.283272	2.266388	2.786143	2.308428
Skewness	0.025018	0.229849	0.257867	0.372647	0.306806	-0.109046	0.171302
Kurtosis	6.204963	5.169968	6.827912	14.03757	5.752171	5.434604	4.997545
Jarque-Bera	325.7807	156.0077	473.0531	3880.574	252.1118	189.4529	130.2440
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	26.24622	13.81800	24.86169	56.57593	13.74590	25.41402	17.33267
Sum Sq. Dev.	5433.118	3872.357	5684.546	8192.704	3903.749	5899.569	4049.919
Observations	761	761	761	761	761	761	761

All kurtosis are higher than 3 (eviews output), skewnesses are greater than zero so jarque-bera statistics seen in Table 5.1 are increasing with increasing kurtosis. All these statistics of returns indicate the non-normalities of distributions. The distribution of time series has very important place because the distribution of return affects VaR figures calculated by historical simulation and monte carlo methods. As see in the next distribution figures, logistic distribution fits all except ICE gasoil futures return, which is distributed as loglogistic distribution. Let's see the return graphs and the distribution of returns.

5.4 Time Series Analysis

5.4.1 Principal Component Analysis

Value at Risk calculation by parametric method requires the standard deviation of the portfolio. To be able to get the standard deviation of portfolio, the variance-covariance matrix of portfolio should be gained and modeled by Multivariate GARCH. The portfolio consists of five physical commodities and two futures contracts so the number of risk factors is seven. The time series modeling of variance-covariance matrix requires 28 elements MGARCH modeling; 7 variances and twenty one covariances. As seen below correlation matrix of portfolio, the correlation between risk factors is very high. The modeling tool for correlated financial systems converting them a few market risk factors is Principal Component Analysis[8] (PCA). PCA is to reduce dimensions so that only most important sources of information are used. The most advantage of using PCA is its providing computational efficiency. It comes from the lack of correlation between the principal components and the dimension reduction from taking just a few of them. The decision about how many principal components are taken by the analyzer depends on the sensitivity of the analysis. It is useful in highly correlated systems because only a few independent sauces of variation (orthogonal to each other) can explain the whole portfolio. After transformation to the principal components application, the factor weights are used to relate the transformations to the original system. This significant reduction is very useful tool in risk management due to saving time.

In this study, PCA is the construction of large positive definite covariance matrices. Here, besides the reduction of matrices, the principal components are orthogonal to each other. If the matrix has n x n dimension, the number of risk factors is n(n+1)/2. In this study, the matrix dimension is 7x7 and it requires 28 different risk factors modeling. Application of PCA in this var-cov matrix gave 7 independent principal components which are orthogonal to each others.

[8] Pls see Chapter 6 in "Market Models" written by Alexander (2001) for the mathematical background of PCA, pg 145-147 and Brummelhuis (2002), Principal Component Value At Risk. Mathematical Finance, Vol. 12, No. 1 (January 2002), 23-43. Moreover, For a good example of PCA usage in VaR analysis by monte carlo method is "Optimization of Monte Carlo Procedures for Value at Risk Estimates" by Antonelli and Iovino (2002), Economic Notes by Banca Monte dei Paschi di Siena SpA, vol. 31, no. 1-2002, pp. 59-78.

Table 5.2 : Principal Component Analysis.

Principal Components Analysis
Date: 07/15/10 Time: 02:09
Sample: 1/01/2007 11/30/2009
Included observations: 761
Computed using: Ordinary correlations
Extracting 7 of 7 possible components

Eigenvalues: (Sum = 7, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	5.576233	5.027481	0.7966	5.576233	0.7966
2	0.548752	0.206581	0.0784	6.124985	0.8750
3	0.342170	0.073136	0.0489	6.467155	0.9239
4	0.269034	0.149756	0.0384	6.736189	0.9623
5	0.119279	0.009447	0.0170	6.855468	0.9794
6	0.109832	0.075132	0.0157	6.965300	0.9950
7	0.034700	---	0.0050	7.000000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
BENZIN	0.367929	-0.199032	0.371677	0.795052	0.077642	0.220724	-0.003984
BRENT	0.402794	0.000337	0.118484	0.012800	-0.027018	-0.907001	0.013209
BRENT_C1	0.302775	0.940395	-0.026218	0.067487	0.037370	0.131362	0.009444
FUEL_OIL	0.364811	-0.094588	0.670936	-0.582674	0.106394	0.238405	0.012089
ICE_C1	0.386881	-0.173494	-0.473144	-0.099174	0.758677	0.086789	0.058299
JET	0.403669	-0.142324	-0.296701	-0.076788	-0.503357	0.164054	0.665271
MOTORIN	0.406201	-0.129380	-0.291683	-0.089071	-0.389316	0.141745	-0.744037

Ordinary correlations:

	BENZIN	BRENT	BRENT_C1	FUEL_OIL	ICE_C1	JET	MOTORIN
BENZIN	1.000000						
BRENT	0.821925	1.000000					
BRENT_C1	0.533112	0.666197	1.000000				
FUEL_OIL	0.726256	0.820482	0.554435	1.000000			
ICE_C1	0.740433	0.838345	0.570756	0.714876	1.000000		
JET	0.788801	0.879936	0.609697	0.770669	0.891845	1.000000	
MOTORIN	0.791302	0.886995	0.620107	0.778496	0.902845	0.964649	1.000000

The first principal component carries 80 % of the total knowledge of portfolio (Table 5.2). The second's carriage capacity is % 8. The last one is 5 %o. The decision of how many principal components are taken depends on the sensitivity of the analysis. The first two principal components carry 88 % of the total knowledge of portfolio. In the study, all principal components are taken for the study. As seen Table 5.2., the big proportion of volatility of portfolio is extracted to first principal component (PC1) (Figure 5.2 and Figure 5.3).

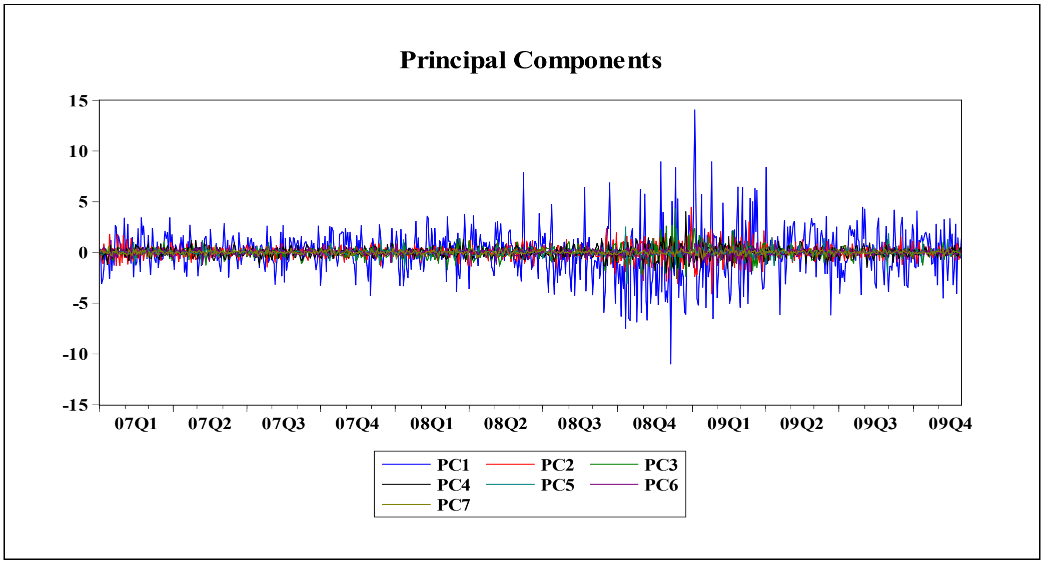

Figure 5.2 : The Volatilities of principal components.

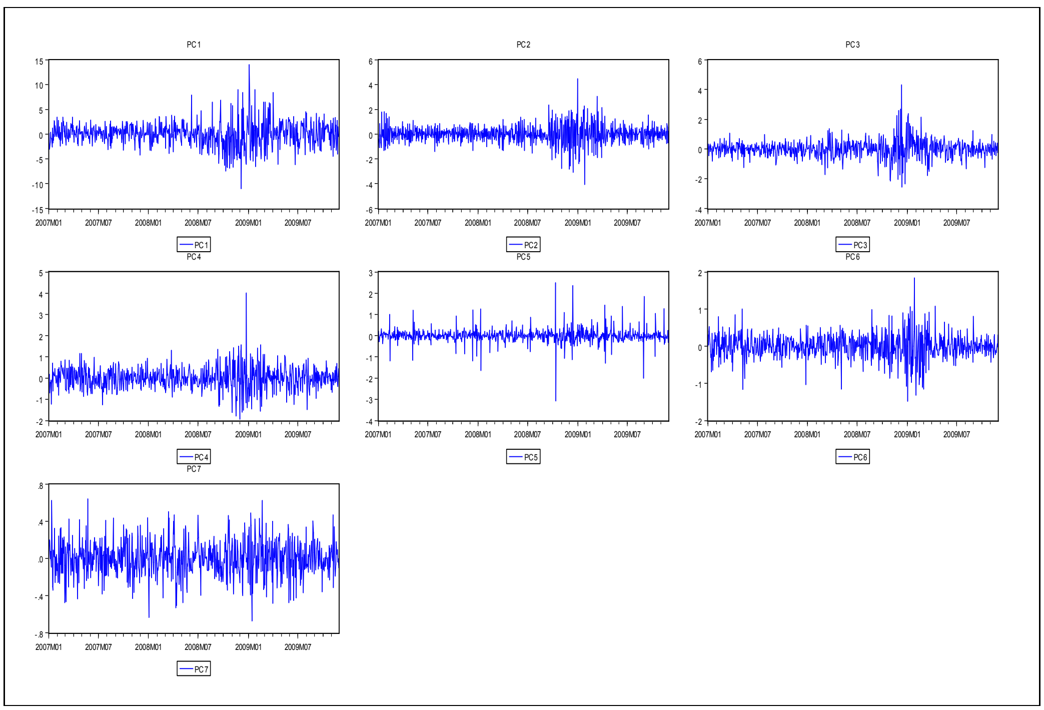

Figure 5.3 : The Volatilities of principal components individually.

5.4.2 Volatility modeling of principal components

General Volatility Equation using GARCH modeling:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{y} \alpha_i \varepsilon_{t-i}^2 + \sum \beta_i \sigma_{t-i}^2 \quad \textbf{(5.2)}$$

The volatility modeling of principal components are given in Appendix B for each principal component individually. For modeling of principal components in Appendix B, the correlograms and statistics of Principal Components (PC), The Mean Equations of PCs, Correlograms and Statistics of PCs' Residuals, Correlogram of PCs' Residuals Squared, Heteroskedasticity Test of PCs, The Volatility and Mean Equation Modelings of PCs, Correlograms of PCs' Standardized Residuals Squared tables are given from Table B.1 to Table B. 46 for each seven principal components and Forecasts of PCs' Variance are given from Figure B.1 to Figure B.8.

- **Volatility Equation of Principal Component 1 (PC1)**

$$\sigma_t^2 = 0.018310 + 0.039379_1 \varepsilon_{t-1}^2 + 0.958242 \sigma_{t-1}^2 \quad \textbf{(5.3)}$$

- **Volatility Equation of Principal Component 2 (PC2)**

$$\sigma_t^2 = 0.006587 + 0.082648_1 \varepsilon_{t-1}^2 + 0.898029 \sigma_{t-1}^2 \quad \textbf{(5.4)}$$

- **Volatility Equation of Principal Component 3 (PC3)**

$$\sigma_t^2 = 0.003542 + 0.147334 \varepsilon_{t-1}^2 - 0.071391 \varepsilon_{t-2}^2 + 0.260464 \sigma_{t-1}^2 + 0.652521 \sigma_{t-2}^2 \quad \textbf{(5.5)}$$

- **Volatility Equation of Principal Component 4 (PC4)**

$$\sigma_t^2 = 0.003238 + 0.062098 \varepsilon_{t-1}^2 + 0.925102 \sigma_{t-1}^2 \quad \textbf{(5.6)}$$

- **Volatility Equation of Principal Component 5 (PC5)**

$$Log(\sigma_t^2) = -0.444674 + 0.782907(abs(\varepsilon_{t-1}^2) / sqrt(\sigma_{t-1}^2)) - 0.714215 abs((\varepsilon_{t-2}^2) / sqrt(\sigma_{t-2}^2) - 0.105493 \varepsilon_{t-1}^2 / sqrt(\sigma_{t-1}^2) + 1.506569 \log(\sigma_{t-1}^2) - 0.659481 \log(\sigma_{t-2}^2) \quad \textbf{(5.7)}$$

- **Volatility Equation of Principal Component 6 (PC6)**

$$\sigma_t^2 = 0.001909 + 0.065068 \varepsilon_{t-1}^2 + 0.914828 \sigma_{t-1}^2 \quad \textbf{(5.8)}$$

- **Volatility Equation of Principal Component 7 (PC7)**

$$\sigma_t^2 = 0.006069 + 0.082686 \varepsilon_{t-1}^2 + 0.742856 \sigma_{t-1}^2 \quad \textbf{(5.9)}$$

5.5 Commodity Volatilities (Transition from Principal Components to Commodities)

After all modeling of principal components' volatility, the variances of commodities should be gained to be able to get var-cov matrix. To get variance of commodities:

Step 1: The first step is to get the commodity equations which have principal components as independent variables. Regression equation gives the commodity equation.

$$Brent = c_1 * pc1 + c_2 * pc2 + ... + c_7 * pc7 \quad \textbf{(5.10)}$$

$$Gasoil = k_1 * pc1 + k_2 * pc2 + ... + k_7 * pc7 \quad \textbf{(5.11)}$$

Step 2: The variances of commodities should be obtained.

$$VAR(Brent) = c_1^2 * VAR(pc1) + c_2^2 * VAR(pc2) + ... + c_7^2 * VAR(pc7) \quad \textbf{(5.12)}$$

$$VAR(Gasoil) = k_1^2 * VAR(pc1) + k_2^2 * VAR(pc2) + ... + k_7^2 * VAR(pc7) \quad \textbf{(5.13)}$$

Step 3: The covariances of commodities should be obtained.

$$COV(Brent, Gasoil) = c_1 k_1 * VAR(pc1) + c_2 k_2 * VAR(pc2) + .. + c_7 k_7 * VAR(pc7) \quad \textbf{(5.14)}$$

5.5.1 Brent

Table 5.3 : Brent equation.

Dependent Variable: BRENT
Method: Least Squares
Date: 12/06/09 Time: 00:51
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.034489	1.66E-17	2.08E+15	0.0000
PC1	1.076256	7.01E-18	1.53E+17	0.0000
PC2	0.000900	2.24E-17	4.03E+13	0.0000
PC3	0.316586	2.83E-17	1.12E+16	0.0000
PC4	0.034202	3.19E-17	1.07E+15	0.0000
PC5	-0.072191	4.79E-17	-1.51E+15	0.0000
PC6	-2.423482	5.00E-17	-4.85E+16	0.0000
PC7	0.035293	8.89E-17	3.97E+14	0.0000

R-squared	1.000000	Mean dependent var	0.034489
Adjusted R-squared	1.000000	S.D. dependent var	2.673731
S.E. of regression	4.57E-16	Sum squared resid	1.57E-28
F-statistic	3.72E+33	Durbin-Watson stat	2.008794
Prob(F-statistic)	0.000000		

$$Brent = 1.076256 * pc1 + 0.000900 * pc2 + 0.316586 * pc3 + 0.034202 * pc4 - 0.072191 * pc5 - 2.423482 * pc6 + 0.035293 * pc7 \quad \textbf{(5.15)}$$

$$VAR(Brent) = 1.076256^2 * var\_pc1 + 0.000900^2 * var\_pc2 + 0.316586^2 * var\_pc3 + 0.034202^2 * var\_pc4 + (-0.072191)^2 * var\_pc5 + (-2.423482)^2 * var\_pc6 + 0.035293^2 * var\_pc7 \quad \textbf{(5.16)}$$

5.5.2 Gasoil

Table 5.4 : Gasoil equation.

Dependent Variable: GASOIL
Method: Least Squares
Date: 03/29/11 Time: 11:07
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018158	1.45E-17	1.25E+15	0.0000
PC1	0.916297	6.14E-18	1.49E+17	0.0000
PC2	-0.291852	1.96E-17	-1.49E+16	0.0000
PC3	-0.657971	2.48E-17	-2.65E+16	0.0000
PC4	-0.200923	2.80E-17	-7.19E+15	0.0000
PC5	-0.878209	4.20E-17	-2.09E+16	0.0000
PC6	0.319744	4.38E-17	7.31E+15	0.0000
PC7	-1.678378	7.79E-17	-2.16E+16	0.0000

R-squared	1.000000	Mean dependent var	0.018158
Adjusted R-squared	1.000000	S.D. dependent var	2.257257
S.E. of regression	4.00E-16	Sum squared resid	1.21E-28
F-statistic	3.46E+33	Durbin-Watson stat	1.910656
Prob(F-statistic)	0.000000		

$$Gasoil = 0.916297 * pc1 - 0.291852 * pc2 - 0.657971 * pc3 - 0.200923 * pc4 - 0.878209 * pc5 + 0.319744 * var\_pc6 - 1.678378 * pc7 \quad \textbf{(5.17)}$$

$$VAR(Gasoil) = 0.916297^2 * var\_pc1 + (-0.291852)^2 * var\_pc2 + (-0.657971)^2 * var\_pc3 + (-0.200923)^2 * var\_pc4 + (-0.878209)^2 * var\_pc5 + 0.319744^2 * var\_pc6 + (-1.678378)^2 * var\_pc7 \quad \textbf{(5.18)}$$

5.5.3 Gasoline

Table 5.5 : Gasoline Equation

Dependent Variable: GASOLINE
Method: Least Squares
Date: 03/29/11 Time: 11:04
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.032670	1.81E-17	1.81E+15	0.0000
PC1	1.005587	7.65E-18	1.31E+17	0.0000
PC2	-0.543975	2.44E-17	-2.23E+16	0.0000
PC3	1.015830	3.09E-17	3.29E+16	0.0000
PC4	2.172956	3.48E-17	6.24E+16	0.0000
PC5	0.212203	5.23E-17	4.06E+15	0.0000
PC6	0.603261	5.45E-17	1.11E+16	0.0000
PC7	-0.010889	9.70E-17	-1.12E+14	0.0000

R-squared	1.000000	Mean dependent var	0.032670
Adjusted R-squared	1.000000	S.D. dependent var	2.734898
S.E. of regression	4.98E-16	Sum squared resid	1.87E-28
F-statistic	3.27E+33	Durbin-Watson stat	1.989127
Prob(F-statistic)	0.000000		

$$\begin{aligned}\text{Gasoline} &= 1.005587 * \text{pc1} - 0.543975 * \text{pc2} + 1.015830 * \text{pc3} + 2.172956 * \text{pc4} \\ &+ 0.212203 * \text{pc5} + 0.603261 * \text{pc6} - 0.010889 * \text{pc7}\end{aligned} \quad \textbf{(5.19)}$$

$$\begin{aligned}\text{VAR(Gasoline)} &= 1.005587\text{^}2 * \text{var\_pc1} + (-0.543975)\text{^}2 * \text{var\_pc2} \\ &+ 1.015830\text{^}2 * \text{var\_pc3} + 2.172956\text{^}2 * \text{var\_pc4} + 0.212203\text{^}2 * \text{var\_pc5} \\ &+ 0.603261\text{^}2 * \text{var\_pc6} + (-0.010889)\text{^}2 * \text{var\_pc7}\end{aligned} \quad \textbf{(5.20)}$$

5.5.4 Fuel Oil

Table 5.6 : Fuel Oil Equation

Dependent Variable: FUEL_OIL
Method: Least Squares
Date: 12/06/09 Time: 00:56
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.074344	1.75E-17	4.24E+15	0.0000
PC1	1.196986	7.43E-18	1.61E+17	0.0000
PC2	-0.310353	2.37E-17	-1.31E+16	0.0000
PC3	2.201416	3.00E-17	7.34E+16	0.0000
PC4	-1.911819	3.38E-17	-5.65E+16	0.0000
PC5	0.349089	5.08E-17	6.87E+15	0.0000
PC6	0.782235	5.30E-17	1.48E+16	0.0000
PC7	0.039665	9.42E-17	4.21E+14	0.0000

R-squared	1.000000	Mean dependent var	0.074344
Adjusted R-squared	1.000000	S.D. dependent var	3.283272
S.E. of regression	4.84E-16	Sum squared resid	1.76E-28
F-statistic	4.99E+33	Durbin-Watson stat	1.981360
Prob(F-statistic)	0.000000		

$$\begin{aligned}\text{Fueloil} &= 1.196986 * pc1 - 0.310353 * pc2 + 2.201416 * pc3 - 1.911819 * pc4 \\ &+ 0.349089 * pc5 + 0.782235 * pc6 + 0.039665 * pc7\end{aligned} \quad \textbf{(5.21)}$$

$$\begin{aligned}\text{VAR(Fuel oil)} &= 1.196986\text{^}2 * var\_pc1 + (-0.310353)\text{^}2 * var\_pc2 \\ &+ 2.201416\text{^}2 * var\_pc3 + (-1.911819)\text{^}2 * var\_pc4 + 0.349089\text{^}2 * var\_pc5 \\ &+ 0.782235\text{^}2 * var\_pc6 + 0.039665\text{^}2 * var\_pc7\end{aligned} \quad \textbf{(5.22)}$$

5.5.5 Jet

Table 5.7 : Jet Equation

Dependent Variable: JET
Method: Least Squares
Date: 12/06/09 Time: 00:58
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018063	8.24E-18	2.19E+15	0.0000
PC1	0.914270	3.49E-18	2.62E+17	0.0000
PC2	-0.322349	1.11E-17	-2.90E+16	0.0000
PC3	-0.671998	1.41E-17	-4.77E+16	0.0000
PC4	-0.173917	1.59E-17	-1.09E+16	0.0000
PC5	-1.140052	2.39E-17	-4.78E+16	0.0000
PC6	0.371567	2.49E-17	1.49E+16	0.0000
PC7	1.506770	4.42E-17	3.41E+16	0.0000

R-squared	1.000000	Mean dependent var	0.018063
Adjusted R-squared	1.000000	S.D. dependent var	2.266388
S.E. of regression	2.27E-16	Sum squared resid	3.89E-29
F-statistic	1.08E+34	Durbin-Watson stat	2.034428
Prob(F-statistic)	0.000000		

$$\text{Jet} = 0.914270 * pc1 - 0.322349 * pc2 - 0.671998 * pc3 - 0.173917 * pc4 - 1.140052 * pc5 + 0.371567 * pc6 + 1.506770 * pc7 \quad \textbf{(5.23)}$$

$$\text{VAR(Jet)} = 0.914270\text{^}2 * var\_pc1 + (-0.322349)\text{^}2 * var\_pc2 + (-0.671998)\text{^}2 * var\_pc3 + (-0.173917)\text{^}2 * var\_pc4 + (-1.140052)\text{^}2 * var\_pc5 + 0.371567\text{^}2 * var\_pc6 + 1.506770\text{^}2 * var\_pc7 \quad \textbf{(5.24)}$$

5.5.6 ICE Brent C1

Table 5.8 : ICE Brent Equation

Dependent Variable: BRENT_C1
Method: Least Squares
Date: 12/06/09 Time: 00:53
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.033396	2.00E-17	1.67E+15	0.0000
PC1	0.843021	8.48E-18	9.94E+16	0.0000
PC2	2.618354	2.70E-17	9.68E+16	0.0000
PC3	-0.072999	3.42E-17	-2.13E+15	0.0000
PC4	0.187904	3.86E-17	4.87E+15	0.0000
PC5	0.104049	5.80E-17	1.79E+15	0.0000
PC6	0.365753	6.04E-17	6.05E+15	0.0000
PC7	0.026295	1.08E-16	2.45E+14	0.0000

R-squared	1.000000	Mean dependent var	0.033396
Adjusted R-squared	1.000000	S.D. dependent var	2.786143
S.E. of regression	5.53E-16	Sum squared resid	2.30E-28
F-statistic	2.76E+33	Durbin-Watson stat	2.124023
Prob(F-statistic)	0.000000		

$$\begin{aligned}\text{Brent C1} &= 0.843021 * \text{pc1} + 2.618354 * \text{pc2} - 0.072999 * \text{pc3} + 0.187904 * \text{pc4} \\ &+ 0.104049 * \text{pc5} + 0.365753 * \text{pc6} + 0.026295 * \text{pc7}\end{aligned} \quad \textbf{(5.25)}$$

$$\begin{aligned}\text{VAR(BrentC1)} &= 0.843021\text{^}2 * \text{var\_pc1} + 2.618354\text{^}2 * \text{var\_pc2} \\ &+ (-0.072999)\text{^}2 * \text{var\_pc3} + 0.187904\text{^}2 * \text{var\_pc4} + 0.104049\text{^}2 * \text{var\_pc5} \\ &+ 0.365753\text{^}2 * \text{var\_pc6} + 0.026295\text{^}2 * \text{var\_pc7}\end{aligned} \quad \textbf{(5.26)}$$

5.5.7 ICE C1

Table 5.9 : ICE Gasoil Equation

Dependent Variable: ICE_C1
Method: Least Squares
Date: 12/06/09 Time: 00:57
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022776	1.97E-17	1.15E+15	0.0000
PC1	0.892501	8.36E-18	1.07E+17	0.0000
PC2	-0.400236	2.66E-17	-1.50E+16	0.0000
PC3	-1.091501	3.37E-17	-3.24E+16	0.0000
PC4	-0.228786	3.80E-17	-6.01E+15	0.0000
PC5	1.750200	5.71E-17	3.06E+16	0.0000
PC6	0.200215	5.95E-17	3.36E+15	0.0000
PC7	0.134491	1.06E-16	1.27E+15	0.0000

R-squared	1.000000	Mean dependent var	0.022776
Adjusted R-squared	1.000000	S.D. dependent var	2.308428
S.E. of regression	5.44E-16	Sum squared resid	2.23E-28
F-statistic	1.95E+33	Durbin-Watson stat	1.932871
Prob(F-statistic)	0.000000		

$$\begin{aligned} \text{IceC1} &= 0.892501 * \text{pc1} - 0.400236 * \text{pc2} - 1.091501 * \text{pc3} - 0.228786 * \text{pc4} \\ &+ 1.750200 * \text{pc5} + 0.200215 * \text{pc6} + 0.134491 * \text{pc7} \end{aligned} \tag{5.27}$$

$$\begin{aligned} &\text{VAR(Ice C1)} = 0.892501\text{\^{}}2 * \text{var\_pc1} + (-0.400236)\text{\^{}}2 * \text{var\_pc2} \\ &+ (-1.091501)\text{\^{}}2 * \text{var\_pc3} + (-0.228786)\text{\^{}}2 * \text{var\_pc4} + 1.750200\text{\^{}}2 * \text{var\_pc5} \\ &+ 0.200215\text{\^{}}2 * \text{var\_pc6} + 0.134491\text{\^{}}2 * \text{var\_pc7} \end{aligned} \tag{5.28}$$

5.6 Commodity Covariances (Transition from Principal Components to Commodities)

$$\begin{aligned} &\text{COV(Gasoline; Brent)} = 1.005 * 1.076 * \text{var\_pc1} - 0.543 * 0.0009 * \text{var\_pc2} \\ &+ 1.0158 * 0.316 * \text{var\_pc3} + 2.172 * 0.0342 * \text{var\_pc4} - 0.212 * 0.0721 * \text{var\_pc5} \\ &- 0.603 * 2.423 * \text{var\_pc6} - 0.0108 * 0.0352 * \text{var\_pc7} \end{aligned} \tag{5.29}$$

$$\begin{aligned} &\text{COV(Gasoline, BrentC1)} = 1.0057 * 0.843 * \text{var\_pc1} - 0.543 * 2.618 * \text{var\_pc2} \\ &- 1.0158 * 0.0729 * \text{var\_pc3} + 2.172 * 0.187 * \text{var\_pc4} + 0.212 * 0.104 * \text{var\_pc5} \\ &+ 0.603 * 0.365 * \text{var\_pc6} - 0.0108 * 0.0262 * \text{var\_pc7} \end{aligned} \tag{5.30}$$

$$\begin{aligned}COV(Gasoline, Fuel\ Oil) &= 1.005*1.1969*var\_pc1 + 0.543*0.310*var\_pc2\\ &+ 1.015*2.201*var\_pc3 - 2.172*1.911*var\_pc4 + 0.212*0.349*var\_pc5\\ &+ 0.603*0.782*var\_pc6 - 0.0108*0.0396*var\_pc7\end{aligned} \tag{5.31}$$

$$\begin{aligned}COV(Gasoline; ICE\ Gasoil) &= 1.005*0.892*var\_pc1 + 0.543*0.400*var\_pc2\\ &- 1.0158*1.0915*var\_pc3 - 2.172*0.228*var\_pc4 + 0.2122*1.750*var\_pc5\\ &+ 0.603*0.200*var\_pc6 - 0.0108*0.134*var\_pc7\end{aligned} \tag{5.32}$$

$$\begin{aligned}COV(Gasoline, Jet) &= 1.005*0.9141*var\_pc1 + 0.543*0.322*var\_pc2\\ &- 1.015*0.671*var\_pc3 - 2.172*0.173*var\_pc4 - 0.212*1.140*var\_pc5\\ &+ 0.603*0.371*var\_pc6 - 0.010*1.506*var\_pc7\end{aligned} \tag{5.33}$$

$$\begin{aligned}COV(Gasoline, Gasoil) &= 1.005*0.916*var\_pc1 + 0.543*0.291*var\_pc2\\ &- 1.015*0.657*var\_pc3 - 2.172*0.200*var\_pc4 - 0.212*0.878*var\_pc5\\ &+ 0.603*0.319*var\_pc6 + 0.010*1.678*var\_pc7\end{aligned} \tag{5.34}$$

$$\begin{aligned}COV(Brent, ICE\ Brent) &= 1.076*0.843*var\_pc1 + 0.0009*2.6186*var\_pc2\\ &- 0.316*0.072*var\_pc3 + 0.034*0.187*var\_pc4 - 0.072*0.104*var\_pc5\\ &- 2.423*0.365*var\_pc6 + 0.035*0.026*var\_pc7\end{aligned} \tag{5.35}$$

$$\begin{aligned}COV(Brent, Fuel\ Oil) &= 1.076*1.196*var\_pc1 - 0.0009*0.310*var\_pc2\\ &+ 0.316*2.201*var\_pc3 - 0.034*1.911*var\_pc4 - 0.072*0.349*var\_pc5\\ &- 2.423*0.782*var\_pc6 + 0.035*0.039*var\_pc7\end{aligned} \tag{5.36}$$

$$\begin{aligned}COV(Brent, ICEGasoil) &= 1.076*0.892*var\_pc1 - 0.0009*0.400*var\_pc2\\ &- 0.316*1.091*var\_pc3 - 0.034*0.228*var\_pc4 - 0.072*1.750*var\_pc5\\ &- 2.423*0.200*var\_pc6 + 0.035*0.134*var\_pc7\end{aligned} \tag{5.37}$$

$$\begin{aligned}COV(Brent, Jet) &= 1.076*0.914*var\_pc1 - 0.0009*0.322*var\_pc2\\ &- 0.316*0.671*var\_pc3 - 0.034*0.173*var\_pc4 + 0.072*1.140*var\_pc5\\ &- 2.423*0.371*var\_pc6 + 0.035*1.506*var\_pc7\end{aligned} \tag{5.38}$$

$$\begin{aligned}COV(Brent, Gasoil) &= 1.076*0.916*var\_pc1 - 0.0009*0.291*var\_pc2\\ &- 0.316*0.657*var\_pc3 - 0.034*0.200*var\_pc4 + 0.072*0.878*var\_pc5\\ &- 2.423*0.319*var\_pc6 - 0.0352*1.678*var\_pc7\end{aligned} \tag{5.39}$$

$$\begin{aligned}COV(ICEBrent, Fuel\_oil) &= 0.843*1.196*var\_pc1 - 2.618*0.310*var\_pc2\\ &- .0721*2.201*var\_pc3 - 0.187*1.911*var\_pc4 + 0.104*0.349*var\_pc5\\ &+ 0.365*0.782*var\_pc6 + 0.026*0.039*var\_pc7\end{aligned} \tag{5.40}$$

$$\begin{aligned}COV(ICEBrent, Jet) &= 0.843*0.914*var\_pc1 - 2.618*0.322*var\_pc2\\ &+ 0.072*0.671*var\_pc3 - 0.187*0.173*var\_pc4 - 0.104*1.140*var\_pc5\\ &+ 0.365*0.371*var\_pc6 + 0.026*1.506*var\_pc7\end{aligned} \tag{5.41}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{ICEBrent},\mathrm{Gasoil}) &= 0.843 * 0.916 * \mathrm{var\_pc1} - 2.618 * 0.291 * \mathrm{var\_pc2} \\ &+ 0.072 * 0.657 * \mathrm{var\_pc3} - 0.187 * 0.200 * \mathrm{var\_pc4} - 0.104 * 0.878 * \mathrm{var\_pc5} \\ &+ 0.365 * 0.319 * \mathrm{var\_pc6} - 0.026 * 1.678 * \mathrm{var\_pc7}\end{aligned} \tag{5.42}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{Fueloil},\mathrm{Gasoil}) &= 1.196 * 0.916 * \mathrm{var\_pc1} + 0.310 * 0.291 * \mathrm{var\_pc2} \\ &- 2.201 * 0.657 * \mathrm{var\_pc3} + 1.911 * 0.200 * \mathrm{var\_pc4} - 0.349 * 0.878 * \mathrm{var\_pc5} \\ &+ 0.782 * 0.319 * \mathrm{var\_pc6} - 0.039 * 1.678 * \mathrm{var\_pc7}\end{aligned} \tag{5.43}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{ICE\ Gasoil},\mathrm{ICE\ Brent}) &= 0.892 * 0.843 * \mathrm{var\_pc1} - 0.400 * 2.618 * \mathrm{var\_pc2} \\ &+ 1.091 * 0.072 * \mathrm{var\_pc3} - 0.228 * 0.187 * \mathrm{var\_pc4} + 1.750 * 0.104 * \mathrm{var\_pc5} \\ &+ 0.200 * 0.365 * \mathrm{var\_pc6} + 0.134 * 0.026 * \mathrm{var\_pc7}\end{aligned} \tag{5.44}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{ICEGasoil},\mathrm{Fueloil}) &= 0.892 * 1.196 * \mathrm{var\_pc1} + 0.400 * 0.310 * \mathrm{var\_pc2} \\ &- 1.091 * 2.201 * \mathrm{var\_pc3} + 0.228 * 1.911 * \mathrm{var\_pc4} + 1.750 * 0.349 * \mathrm{var\_pc5} \\ &+ 0.200 * 0.782 * \mathrm{var\_pc6} + 0.134 * 0.039 * \mathrm{var\_pc7}\end{aligned} \tag{5.45}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{ICEGasoil},\mathrm{Jet}) &= 0.892 * 0.914 * \mathrm{var\_pc1} + 0.400 * 0.322 * \mathrm{var\_pc2} \\ &+ 1.091 * 0.671 * \mathrm{var\_pc3} + 0.228 * 0.173 * \mathrm{var\_pc4} - 1.750 * 1.140 * \mathrm{var\_pc5} \\ &+ 0.200 * 0.371 * \mathrm{var\_pc6} + 0.134 * 1.506 * \mathrm{var\_pc7}\end{aligned} \tag{5.46}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{ICEGasoil},\mathrm{Gasoil}) &= 0.892 * 0.916 * \mathrm{var\_pc1} + 0.400 * 0.291 * \mathrm{var\_pc2} \\ &+ 1.091 * 0.657 * \mathrm{var\_pc3} + 0.228 * 0.200 * \mathrm{var\_pc4} - 1.750 * 0.878 * \mathrm{var\_pc5} \\ &+ 0.200 * 0.319 * \mathrm{var\_pc6} - 0.134 * 1.678 * \mathrm{var\_pc7}\end{aligned} \tag{5.47}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{Jet},\mathrm{Fuel\ oil}) &= 0.9142 * 1.196 * \mathrm{var\_pc1} + 0.322 * 0.310 * \mathrm{var\_pc2} \\ &- 0.671 * 2.201 * \mathrm{var\_pc3} + 0.173 * 1.911 * \mathrm{var\_pc4} - 1.140 * 0.349 * \mathrm{var\_pc5} \\ &+ 0.371 * 0.782 * \mathrm{var\_pc6} + 1.506 * 0.039 * \mathrm{var\_pc7}\end{aligned} \tag{5.48}$$

$$\begin{aligned}\mathrm{COV}(\mathrm{Jet},\mathrm{Gasoil}) &= 0.914 * 0.91677 * \mathrm{var\_pc1} + 0.322 * 0.291 * \mathrm{var\_pc2} \\ &+ 0.671 * 0.657 * \mathrm{var\_pc3} + 0.173 * 0.200 * \mathrm{var\_pc4} + 1.140 * 0.878 * \mathrm{var\_pc5} \\ &+ 0.371 * 0.319 * \mathrm{var\_pc6} - 1.506 * 1.678 * \mathrm{var\_pc7}\end{aligned} \tag{5.49}$$

5.7 Variance-Covariance Matrix of Portfolio as of Nov 30th 2009

For 30 different days, var-cov matrixes are obtained to use in the calculation of VaR by parametric methodology. The below Table.5.10 is seen as an example for var-cov matrix.

Table 5.10 : Var-Cov matrix[9] as of 30 Nov 2009.

	Gasoil	Gasoline	Fuel Oil	Jet	Brent	ICE Gasoil	ICE Brent
Gasoil	0.00044	0.00044	0.00053	0.00043	0.00048	0.00040	0.00037
Gasoline	0.00044	0.00059	0.00058	0.00044	0.00054	0.00043	0.00040
Fuel Oil	0.00053	0.00058	0.00084	0.00052	0.00064	0.00051	0.00048
Jet	0.00043	0.00044	0.00052	0.00044	0.00048	0.00040	0.00037
Brent	0.00048	0.00054	0.00064	0.00048	0.00060	0.00047	0.00045
ICE Gasoil	0.00040	0.00043	0.00051	0.00040	0.00047	0.00045	0.00036
ICE Brent	0.00037	0.00040	0.00048	0.00037	0.00045	0.00036	0.00049

5.8 Value at Risk Calculation

To be able to mitigate the risks, the quantification of risks is the main issue. Value at Risk is very common used tool for risk measurement.

5.8.1 VaR by Historical Simulation

As mentioned as in VaR section, historical simulation requires full valuation. It means that it consists of going back in time with current portfolio to a time series of historical asset returns. The actual distributions for the data are being used so it does not depend on any assumption. This method considers fat tails and it is independent of model risk. The only assumption is that the futures can be generated by historical return movements.

[9] The gained variance figure is divided by 10,000 because the returns is multipled by 100 at the beginning of time series analysis.

Application:

Step1: Daily returns of commodities and futures contracts for the last two years.

Table 5.11 : Daily returns of commodities and futures contracts.

	Pysical Stocks					Hedging (ICE)	
Date	Gasoil Return	Gasoline Return	Fuel oil Return	Jet Return	Brent Return	ICE Gasoil Return	ICE Brent Return
26.12.2007	0,000000	0,000000	0,000000	0,000000	0,033796	0,015541	0,013288
27.12.2007	0,030171	0,049647	0,016389	0,035374	0,013539	0,004734	0,008902
28.12.2007	-0,014972	0,018145	0,014469	-0,001697	0,000938	-0,002364	-0,009541
31.12.2007	0,000000	0,000000	0,000000	0,000000	0,000000	-0,006828	-0,000320
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
24.11.2009	-0,040723	-0,050855	-0,043059	-0,037726	-0,038625	-0,043096	-0,012994
25.11.2009	0,013489	0,001822	0,021482	0,011967	0,017250	0,012387	0,025566
26.11.2009	-0,002846	0,009784	0,010570	-0,003460	-0,000784	0,002459	-0,018658
27.11.2009	-0,000407	0,000000	-0,021819	-0,002699	-0,005700	-0,009459	0,002465
30.11.2009	0,016162	0,010761	0,015713	0,013042	0,006614	0,015174	0,016576

Step2: Determination of risk factor's weights.

Table 5.12 : Risk Factors' weight in the portfolio.

Commodity	Physical Stock(mton)	Price (USD)/ton	PV (USD)	Weight
Gasoil	**40.000**	**624**	**24.950.000**	**41,5%**
Gasoline	**10.000**	**701**	**7.007.500**	**11,7%**
Fuel oil	**10.000**	**449**	**4.490.000**	**7,5%**
Jet	**10.000**	**656**	**6.560.000**	**10,9%**
Brent	**30.000**	**571**	**17.122.335**	**28,5%**
Total Pyhsical Stock	**100.000**		**60.129.835**	
Ice Gasoil (C1)	**70.000**	**614**	**42.997.500**	**71,0%**
Ice Brent (C1)	**30.000**	**585**	**17.538.045**	**29,0%**
Ice Total	**100.000**		**60.535.545**	

W_{gasoil} : 41.5% W_{jet} : 10.9%

$W_{gasoiline}$: 11.5% $W_{IceBrent}$: 29.0%

$W_{fueloil}$: 7.5% $W_{IceGasoil}$: 71.0%

W_{brent} : 28.5%

Step3: In full valuation, the methodology consist of going back in time and applying current weights to a time series of historical asset return.

$$R_{p,k}=\sum_{i=1}^{N} w_{i,t} R_{i,k} \qquad \textbf{(5.50)}$$

k=1,2,..........,t. & w_t: the weights at their current values

Table 5.13 : Portfolio returns.

		Daily P/L (USD)		
Weighted Pysical Return (%)	ICE Gas+Brent Return(%)	Pyhsical Stock Return(USD)	ICE Portfolio Return(USD	Portfolio Return (USD)
0,009624	0,014888	578.665	901.277	-322.612,77
0,027243	0,005941	1.638.117	359.665	1.278.451,60
-0,002935	-0,004443	-176.501	-268.980	92.479,09
0,000000	-0,004942	0	-299.192	299.191,86
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
-0,041154	-0,034375	-2.474.590	-2.080.913	-393.677,08
0,013631	0,016205	819.631	980.976	-161.344,88
0,000148	-0,003659	8.903	-221.501	230.404,62
-0,003716	-0,006005	-223.423	-363.496	140.073,00
0,012440	0,015580	747.993	943.136	-195.142,65

Step 4: Sorting of P/L of portfolio. The below histogram shows the portfolio P/L distribution. VaR figure is the figure at required confidence level, 95% or 99%.

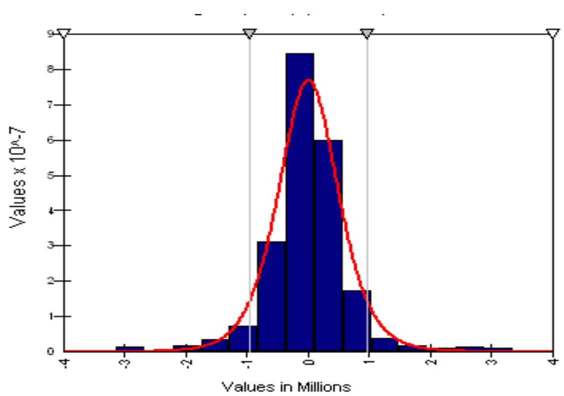

Figure 5.4 : P/L histogram of portfolio.

Daily VaR at 95 % Confidence Level is 951,673 USD. Monthly VaR is calculated by using square root of time and it is 4,361,115.

5.8.2 VaR by Parametric (Variance-Covariance)

In the study, the portfolio consists of seven commodities; five physical commodities and two hedging instruments. In parametric methodology, VaR is calculated;

$$VaR = PV x \sigma_{portfolio} x Z x \sqrt{T}$$

PV : Present value of the portfolio as of required date

σ : Volatility (Standard deviation) of the portfolio

z : Standard score indicating how many standard deviations an observation is above or below the mean

T : Time horizon (days)

Different from historical simulation, in parametric methodology, VaR calculation of portfolio depend on normality assumption of portfolio's return distribution. "Z" score comes from normality assumption.

Application

Step 1: Calculation of standard deviation (volatility-square root of variance) of portfolio. The var-cov matrix is given in time series analysis section as of 30 Nov 2009.

$$\sigma_p = \begin{vmatrix} w_b & w_g & w_{gline} & w_f & w_j & w_{IceG} & w_{IceB} \end{vmatrix} x \begin{vmatrix} \mathrm{var}_b & & & & & & \\ \mathrm{cov}_{b,g} & \mathrm{var}_g & & & & & \\ \mathrm{cov}_{b,gl} & \mathrm{cov}_{gl,g} & \mathrm{var}_{gline} & & & & \\ \mathrm{cov}_{b,f} & \mathrm{cov}_{f,g} & \mathrm{cov}_{f,gl} & \mathrm{var}_f & & & \\ \mathrm{cov}_{b,j} & \mathrm{cov}_{j,g} & \mathrm{cov}_{j,gl} & \mathrm{cov}_{j,f} & \mathrm{var}_j & & \\ \mathrm{cov}_{b,IG} & \mathrm{cov}_{IG,g} & \mathrm{cov}_{IG,gl} & \mathrm{cov}_{IG,f} & \mathrm{cov}_{IG,j} & \mathrm{var}_{IceG} & \\ \mathrm{cov}_{b,IB} & \mathrm{cov}_{IB,g} & \mathrm{cov}_{IB,gl} & \mathrm{cov}_{IB,f} & \mathrm{cov}_{IB,j} & \mathrm{cov}_{IB,IG} & \mathrm{var}_{IceB} \end{vmatrix} x \begin{vmatrix} w_b \\ w_g \\ w_{gline} \\ w_f \\ w_j \\ w_{IceG} \\ w_{IceB} \end{vmatrix} \quad \textbf{(5.51)}$$

Eq. 5.51 is the formula of the var-cov matrix of portfolio.

Parameter definition and value of weights[10]:

w_b : The weight of Brent in the portfolio; 20.7 %

w_g : The weight of Gasoil in the portfolio; 5.8 %

w_{gline} : The weight of Gasoline in the portfolio; 3.7 %

[10] The weights are shown in Table.xxx

w_f : The weight of Fuel oil in the portfolio; 5.4 %

w_j : The weight of Jet in the portfolio; 14.2 %

w_{IceG} : The weight of ICE Gasoil (C1) in the portfolio; -35.6 %

w_{IceB} : The weight of ICE Brent (C1) in the portfolio; -14.5 %

var : variance of commodity[11]

cov : covariance between two commodities[12]

As of 30 Nov 2009;

Weights of risk factors in the portfolio is seen in Table 5.14.

Table 5.14 : The weights of risk factors in the portfolio as of Nov 30th 2009.

Commodity	Physical Stock(mton)	Price (USD)/ton	PV (USD)	Weight
Gasoil	40.000	624	24.950.000	20,7%
Gasoline	10.000	701	7.007.500	5,8%
Fuel oil	10.000	449	4.490.000	3,7%
Jet	10.000	656	6.560.000	5,4%
Brent	30.000	571	17.122.335	14,2%
Total Pyhsical Stock	100.000		60.129.835	
Ice Gasoil (C1)	70.000	614	42.997.500	-35,6%
Ice Brent (C1)	30.000	585	17.538.045	-14,5%
Ice Total	100.000		60.535.545	
PV of Portfolio (USD)			120.665.380	

Application of Matrix Multiplication;

Table 5.15 : Matrix multiplication of the portfolio.

[illegible]

^{11} var_x represent variance of commodity whose name starts with "x" initial. For gasoline, "gline". "I" refers to ICE, "IG" refers to ICE Gasoil, "IB" refers to ICE Brent.

^{12} $cov_{x,y}$ represent covariance between the commodity whose name starts with "x"and "y" initials. For gasoline, "gline".

The square root of result coming from matrix multiplication gives the standard deviation of portfolio, which is equal to 0.003912598 (Table 5.15).

Step 2: Calculation of VaR.

$$VaR = PVx\sigma_{portfolio}xZx\sqrt{T}$$

PV : 120,665,380

$\sigma_{portfolio}$: 0.003912598

z : 1.65 at 95 % Confidence Level

T : One month (21 business-trading days)

VaR at 95 % Confidence Interval is 3,569,780 USD.

5.8.3 VaR by Monte Carlo

Step 1: The return distributions of commodities are determined. The distributions of commodities are given in time series section. Logistic distribution[13] fits all return distributions except jet which is distributed as loglogistic[14] (Table 5.16).

Table 5.16 : Parameters of commodity and futures contracts' distribution.

Commodity	**Distribution Parameters**
Gasoil	RiskLogistic(-0.000792806617406194; 0.0140843427343605)
Gasoline	RiskLoglogistic(-3.14726927740142; 3.14714227665731; 195.58815463966)
Fuel oil	RiskLogistic(-0.000163715870172054; 0.0183715742471977)
Jet	RiskLoglogistic(-0.59259220142927;0.591645740093055; 41.85731804594)
Brent	RiskLogistic(-0.000287737074295243; 0.0160496706230018)
ICE Gasoil	RiskLogistic(-0.000671906496334709; 0.0143012189186393)
ICE Brent	RiskLogistic(-0.000027008320571784; 0.0171061896271453)

[13] The logistic distribution is a continuous probability distribution. It resembles the normal distribution in shape but has heavier tails (higher kurtosis). As we see in descriptive statistics in time series section. There are two parameters; "μ" the mean, and "s" a parameter proportional to the standard deviation.

[14] The log-logistic distribution is a continuous probability distribution for a non-negative random variable. It is the probability distribution of a random variable whose logarithm has a logistic distribution. It is similar in shape to the log-normal distribution but has heavier tails. There are two parameters; "α"median, scale parameter; "β " shape parameter. The parameters α and β are greater than zero. The distribution is unimodal when β > 1 and its dispersion decreases as β increases.

Step 2: Correlation matrix of portfolio is determined to generate random variables regarding the correlation between risk factors.

Table 5.17 : Correlation matrix of portfolio.

	Gasoil	Gasoline	Fuel oil	Jet	Brent	ICE Gasoil	ICE Brent
Gasoil	1	0,80528	0,79102	0,97210	0,89673	0,91098	0,64438
Gasoline	0,80528	1	0,75384	0,80097	0,83943	0,75338	0,55680
Fuel oil	0,79102	0,75384	1	0,77988	0,83796	0,72401	0,57750
Jet	0,97210	0,80097	0,77988	1	0,88623	0,89894	0,63417
Brent	0,89673	0,83943	0,83796	0,88623	1	0,84196	0,68855
ICE Gasoil	0,91098	0,75338	0,72401	0,89894	0,84196	1	0,59533
ICE Brent	0,64438	0,55680	0,57750	0,63417	0,68855	0,59533	1

Step 3: Generation of random prices and modeled P/L of portfolio.

- The prices of commodities for 21 consecutive days (one month) are generated individually by their own distribution regarding correlation among commodities in the portfolio by the simulation of 10,000 times using @Risk[15]. For example; $P_{t+1(Gasoil)}$=

  $P_{t(Gasoil)}$*(1+RiskLogistic(-0.000792806617406194;0.0140843427343605; RiskCorrmat(INDIRECT(Korelasyon!Q2);1))). P_{Gasoil} represents the price of gasoil at the beginning of month. The last part of formula provides the random price generation regarding the correlation among commodities in the portfolio.

- Then, P/L of the portfolio is calculated. The output definitions of monte carlo simulation are described. At the end of simulation, the figure at 95 and 99 % confidence level is the value of VaR at 95 and 99 % confidence level, respectively.

The VaR at 95 % confidence interval as of 31 Nov 2009 is 4,787,056.

[15] @RISK performs risk analysis using Monte Carlo simulation to show you many possible outcomes in your Microsoft Excel spreadsheet. Before run @RISK, the model shoul be done in excel. For detailed information, pls look http://www.palisade.com/risk/ website and Palisade (2004, 2005, 2006).

5.9 VaR Comparisons

Table 5.18 : VaR comparison as of Nov 30th 2009.

Method	**VaR at 95 % Confidence Interval**
Historical Simulation	4,361,115
Parametric	3,569,780
Monte Carlo	4,787,056

In all methods, physical stocks are considered as long position and ICE futures contacts are considered as short position. Parametric method assumes the normal distribution of returns. In our case, as mentioned in the descriptive statistics, all return series of commodities have high kurtosis[16]. Moreover, all of distributions are logistic except jet having loglogistic distribution. These two factors are indicators of heavy tails. As expected, VaR calculated by parametric method is much more less than those calculated by historical simulation and monte carlo methods due to the assumption of normal distribution. The VaR figures calculated by historical simulation and monte carlo method are very close to each other because two methods use commodities own distributions. Using parametric method in time series having fat tailed distribution decreases VaR as seen in our case.

In the thesis, VaR calculations of portfolio are executed for 30 randomly chosen dates at two different confidence intervals; 95% and 99%. All VaR figures of the portfolio having 100% hedge ratio at both 95% and 99% confidence intervals strongly support the above mentioned fact that VaR calculated by parametric method is less than those calculated by historical simulation and monte carlo methods if the time series does not fit normal distribution.

5.10 Optimal Hedge Ratio Analysis

In the thesis, to be able to determine optimal hedge ratio for the portfolio which consists of gasoil, gasoline, Brent, fuel oil and jet commodity as a physical stock and

[16] Marzo and Zagaglia (2007) studied the forecasting properties of linear GARCH models for closing-day futures
prices on crude oil. In order to account for fat tails in the empirical distribution of the series, we compare models based on the normal, Student's t and Generalized Exponential distribution. "Volatility forecasting for crude oil futures", Universit`a di Bologna and Johns Hopkins University and BI Norwegian School of Management and Stockholm University.

ICE gasoil and Brent contracts as a hedging instruments minimum VaR approach is used.

The hedge ratio of ICE contracts in the portfolio is increased by 5 % of pyhsical stock and at each level, VaR figures of portfolio are calculated by three methods; historical simulation, parametric and monte carlo for 30 different randomly chosen date. In Table 5.19, VaR figures for Nov 30th 2009 at 5% increased hedge ratios are given. Min VaR hedge ratios calculated by historical simulation, parametric and monte carlo methos respectively are 100%, 100% and 95 % (Figure 5.5).

Hedge ratio “0” represents no hedge. Hedge efficiencies of three models at min VaR hedge ratios are 64%, 65% and 59% for historical simulation, parametric and monte carlo respectively.

Table 5.19 : Min VaR hedge ratio as of Nov 30th 09 at 95 confidence level (Mio USD).

Hedge Ratio	Historical Simulation	Parametric	Monte Carlo
0%	12.1	10.1	11.7
5%	11.5	9.7	11.2
10%	11.0	9.2	10.7
15%	10.7	8.8	10.2
20%	10.3	8.4	9.7
25%	9.7	8.0	9.2
30%	9.2	7.6	8.7
35%	8.6	7.1	8.2
40%	8.2	6.7	7.7
45%	7.6	6.4	7.3
50%	6.9	6.0	6.8
55%	6.5	5.6	6.5
60%	6.3	5.3	6.1
65%	5.9	4.9	5.7
70%	5.5	4.6	5.5
75%	5.6	4.3	5.2
80%	5.2	4.1	5.0
85%	4.9	3.9	4.9
90%	4.8	3.7	4.8
95%	4.4	3.6	4.8
100%	4.4	3.6	4.9
105%	4.3	3.6	5.0
110%	4.4	3.7	5.1
115%	4.8	3.8	5.4
120%	5.0	4.0	5.6
125%	5.4	4.2	6.0
130%	5.9	4.5	6.3

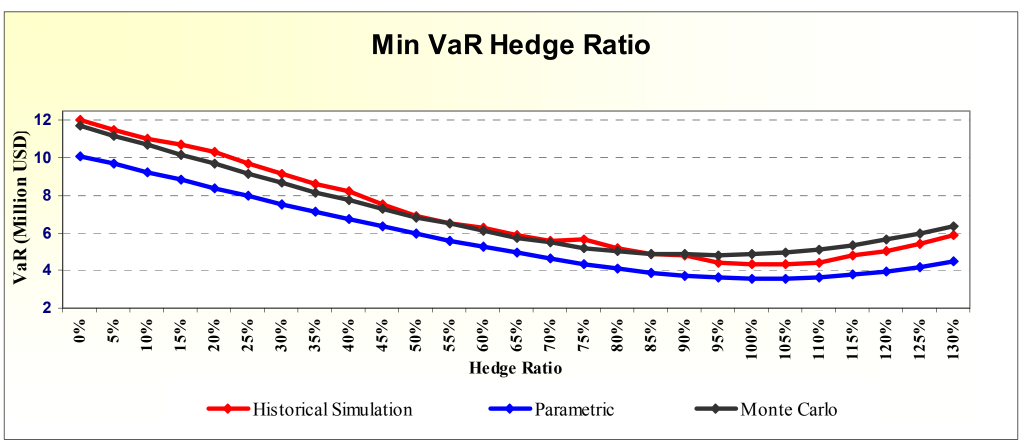

Figure 5.5 : Min VaR hedge ratio graph.

5.11 Value at Risk Analysis Results

In Table 5.20 and Table 5.22, the hedge ratios at min VaR at 95 and 99 % Confidence Level are given subsequently for randomly chosen 30 different dates. In Table 5.21 and Table 5.23, the hedge efficiencies at min VaR at 95 and 99 % Confidence Level are given subsequently.

Table 5.20 : Hedge ratio at min VaR at 95 % confidence level.

Hedge Ratio at Min VaR at 95% Confidence Level							
Date	**Historical**	**Parametric**	**Monte Carlo**	**Date**	**Historical**	**Parametric**	**Monte Carlo**
02.01.2009	90%	90%	80%	23.06.2009	105%	100%	90%
12.01.2009	95%	95%	85%	07.07.2009	100%	100%	90%
22.01.2009	105%	95%	90%	17.07.2009	105%	100%	95%
03.02.2009	90%	95%	90%	28.07.2009	100%	100%	90%
13.02.2009	95%	100%	90%	10.08.2009	105%	100%	95%
26.02.2009	100%	100%	95%	19.08.2009	105%	100%	95%
10.03.2009	100%	100%	90%	27.08.2009	105%	100%	90%
19.03.2009	95%	95%	90%	03.09.2009	105%	100%	95%
31.03.2009	95%	100%	90%	11.09.2009	105%	100%	95%
15.04.2009	105%	100%	95%	17.09.2009	100%	100%	95%
28.04.2009	105%	100%	95%	02.10.2009	95%	95%	85%
08.05.2009	105%	100%	90%	07.10.2009	105%	95%	90%
20.05.2009	105%	100%	95%	16.10.2009	95%	100%	90%
02.06.2009	105%	100%	95%	20.11.2009	105%	100%	95%
11.06.2009	100%	105%	95%	30.11.2009	105%	100%	95%

Table 5.21 : Hedge efficiency at min VaR at 95 % confidence level.

Hedge Efficiency at Min VaR							
Date	**Historical**	**Parametric**	**Monte Carlo**	**Date**	**Historical**	**Parametric**	**Monte Carlo**
02.01.2009	68%	65%	56%	23.06.2009	66%	65%	59%
12.01.2009	70%	64%	58%	07.07.2009	66%	65%	60%
22.01.2009	71%	65%	59%	17.07.2009	66%	65%	59%
03.02.2009	71%	65%	59%	28.07.2009	66%	65%	59%
13.02.2009	69%	65%	59%	10.08.2009	66%	65%	59%
26.02.2009	68%	65%	60%	19.08.2009	66%	65%	60%
10.03.2009	68%	65%	60%	27.08.2009	65%	65%	59%
19.03.2009	68%	65%	60%	03.09.2009	65%	65%	58%
31.03.2009	67%	65%	60%	11.09.2009	65%	65%	58%
15.04.2009	66%	65%	60%	17.09.2009	65%	65%	59%
28.04.2009	67%	65%	60%	02.10.2009	70%	64%	58%
08.05.2009	66%	65%	59%	07.10.2009	71%	65%	59%
20.05.2009	65%	65%	60%	16.10.2009	65%	65%	59%
02.06.2009	66%	65%	59%	20.11.2009	64%	65%	58%
11.06.2009	66%	65%	58%	30.11.2009	64%	65%	59%

Table 5.22 : Hedge ratio at min VaR at 99 % confidence level.

Hedge Ratio at Min VaR at 99% Confidence Level							
Date	**Historical**	**Parametric**	**Monte Carlo**	**Date**	**Historical**	**Parametric**	**Monte Carlo**
02.01.2009	90%	90%	80%	23.06.2009	105%	100%	90%
12.01.2009	95%	95%	80%	07.07.2009	100%	100%	85%
22.01.2009	105%	95%	85%	17.07.2009	105%	100%	90%
03.02.2009	90%	95%	85%	28.07.2009	100%	100%	85%
13.02.2009	95%	100%	85%	10.08.2009	105%	100%	85%
26.02.2009	100%	100%	90%	19.08.2009	105%	100%	90%
10.03.2009	100%	100%	90%	27.08.2009	105%	100%	85%
19.03.2009	95%	95%	85%	03.09.2009	105%	100%	90%
31.03.2009	95%	100%	90%	11.09.2009	105%	100%	85%
15.04.2009	105%	100%	90%	17.09.2009	100%	100%	90%
28.04.2009	105%	100%	90%	02.10.2009	95%	95%	80%
08.05.2009	105%	100%	85%	07.10.2009	105%	95%	85%
20.05.2009	105%	100%	90%	16.10.2009	95%	100%	85%
02.06.2009	105%	100%	95%	20.11.2009	105%	100%	85%
11.06.2009	100%	105%	90%	30.11.2009	105%	100%	90%

Table 5.23 : Hedge efficiency at min VaR at 99 % confidence level.

Hedge Efficiency at Min VaR			
Date	**Historical**	**Parametric**	**Monte Carlo**
02.01.2009	68%	65%	54%
12.01.2009	70%	64%	58%
22.01.2009	71%	65%	58%
03.02.2009	71%	65%	57%
13.02.2009	69%	65%	56%
26.02.2009	68%	65%	58%
10.03.2009	68%	65%	58%
19.03.2009	68%	65%	58%
31.03.2009	67%	65%	59%
15.04.2009	66%	65%	58%
28.04.2009	67%	65%	57%
08.05.2009	66%	65%	58%
20.05.2009	65%	65%	58%
02.06.2009	66%	65%	56%
11.06.2009	66%	65%	58%
23.06.2009	66%	65%	58%
07.07.2009	66%	65%	57%
17.07.2009	66%	65%	58%
28.07.2009	66%	65%	56%
10.08.2009	66%	65%	58%
19.08.2009	66%	65%	58%
27.08.2009	65%	65%	58%
03.09.2009	65%	65%	55%
11.09.2009	65%	65%	56%
17.09.2009	65%	65%	57%
02.10.2009	70%	64%	58%
07.10.2009	71%	65%	58%
16.10.2009	65%	65%	56%
20.11.2009	64%	65%	56%
30.11.2009	64%	65%	58%

The min VaR hedge ratios and hedge efficiencies are coherent with each other regarding different days and different confidence level. All hedge ratios determined by three methods are very close to each other and “95 %” can be representative. Hedge efficiencies of three methods are also close to each other and high; 65 % as an average. The least performed model is monte carlo; 58% approximately.

6. CONCLUSION

The portfolio of energy company consists of five major energy commodities; gasoil, gasoline, fuel oil, jet and crude oil. Because of high volatility of commodity returns and long position with physical stocks, the Company has to be exposed to price risk coming from price decrease potential. To be able to mitigate price risk, the hedging decision regarding the selection of hedge instruments and hedge ratio is important concern for energy companies. In the thesis, underlying assets to futures contracts are chosen as gasoil and Brent crude oil due to high depth and liquidity and high correlation with physical commodities in portfolio. Brent crude oil in the portfolio is hedged with its futures derivative on ICE and the rest of portfolio as of 70 % in terms of weight is hedged with gasoil futures contract ICE. Minimum VaR approach is executed in determination of optimal hedge ratio. VaR is calculated by three methods; historical simulation, variance-covariance and monte carlo method. In parametric VaR assessment, the dimension of variance-covariance matrix is shrinkaged by Principal Component Analysis and volatility is modeled by Multivariate GARCH. At the end of assessment, optimal hedge ratio and hedge efficiencies of three methods are compared with each other. Consequently, hedge efficiency will determine the contribution of risk management techniques into Energy Company.

In the thesis, the mark-to market value of portfolio has been evaluated by Platts product prices. Daily spot prices relative to five major energy commodities: Platts Gasoil, Platts Gasoline, Platts Fuel oil, Platts Jet, Brent crude oil and futures prices relative to two energy futures contracts: ICE Gasoil Futures and ICE crude oil are used. The sample covers the period from January 2007 to November 2009, resulting in 761 daily observations for volatility modeling.

The VaR analysis was executed by three methods; historical, parametric (variance-covariance-RiskMetrics) and monte carlo. For the parametric method, the standard deviation of the portfolio should have been determined. To be able to calculate the standard deviation of the portfolio, the variance covariance matrix has been modeled in terms of mean and volatility modeling. There are 28 elements in the var-cov matrix; 7 variances and 21 covariances. To be able to reduce the number of factors in var-cov matrix, Principal Component Analysis method is used and 7 principal components are being generated; first, second and the last principal components carrying 80%, 8% and 0.5% of knowledge in the portfolio, respectively.

Multivariate GARCH method is used for volatility modeling. All principal components are modeled by GARCH then the transition of variance and covariances to original commodities and ICE instruments are executed. Consequently, the variance-covariance matrix of portfolio is obtained to be used in VaR calculation by parametric method.

The determination of optimal hedge ratio is the main issue. Minimum VaR approach is used in this process. All VaR figures of portfolio in which the hedge ratio of futures position is increased by 5 % are calculated by three methods for randomly determined 30 different days at both 95 and 99 % Confidence Intervals. All results are coherent (logical and consistent) with each other regarding different days and different confidence level.

All time series (returns of commodities) have fat tails and logistic distribution is the best fitting one to all of them except jet, which has loglogistic distribution. Parametric method depends on the assumption that returns are normally distributed. High kurtosis and best fitting distributions disprove the normality assumption of portfolio returns but all VaR figures calculated by parametric method besides historical simulation and monte carlo. Regarding overall result, it can be concluded that VaR figures calculated by parametric method especially for 95% confidence level as expected theoretically is a little bit less than those calculated by historical and monte carlo methods because of fat tails. Moreover, all hedge ratios determined by three methods are very close to each other and “95 %” can be representative. Hedge efficiencies of three methods are also close to each other and high; 65 % as an average. The least performed model is monte carlo; 58% approximately. Close hedge ratios at min VaR and hedge efficiencies strongly advocate the coherence of models. High efficiencies give information about the contribution of risk management into an energy company.

In the light of above mentioned figures, it can be concluded that price risk management has a vital importance in risk mitigation against price risk. The efficiency (hedge performance) can be high if the hedging instrument and optimal hedge ratio is determined correctly. The optimal hedge ratio decision regarding return/risk can be further research subject.

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APPENDICES

APPENDIX A : The Distributions of Returns

APPENDIX B : The Volatility Modeling of Principal Components

APPENDIX A : The Distributions of Returns

Brent

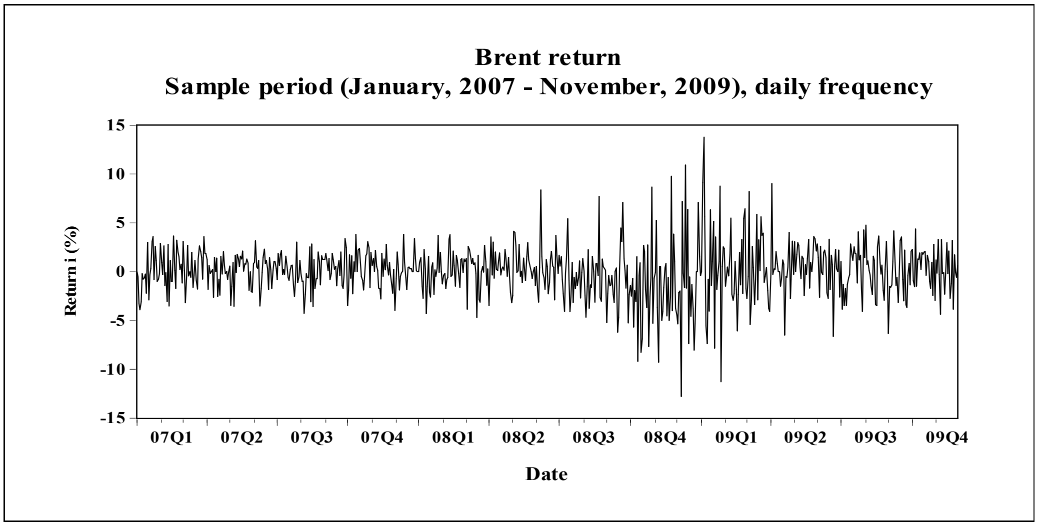


Figure A. 1 : Volatility of Brent return.

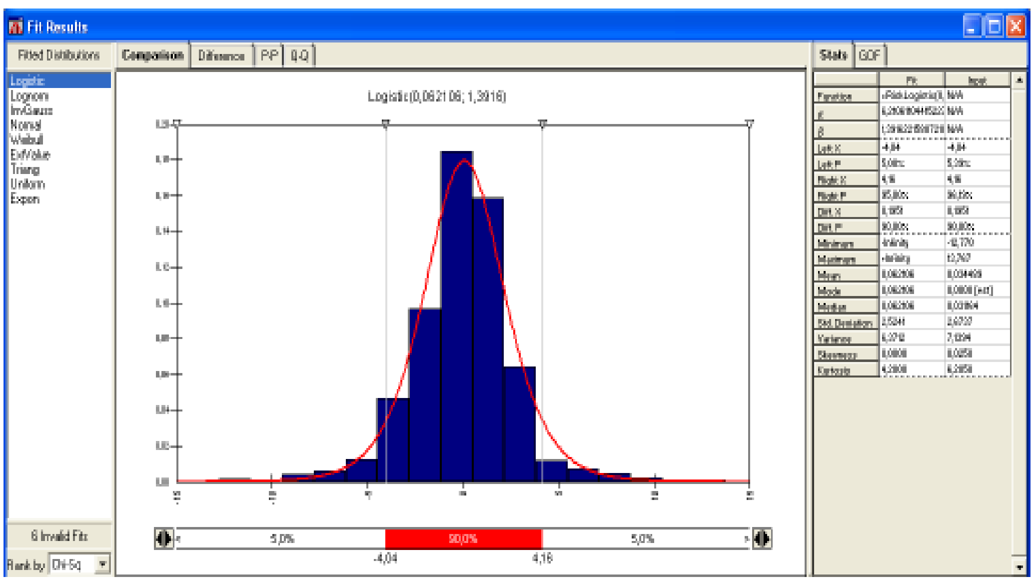


Figure A. 2 : Brent return distribution.

Gasoil

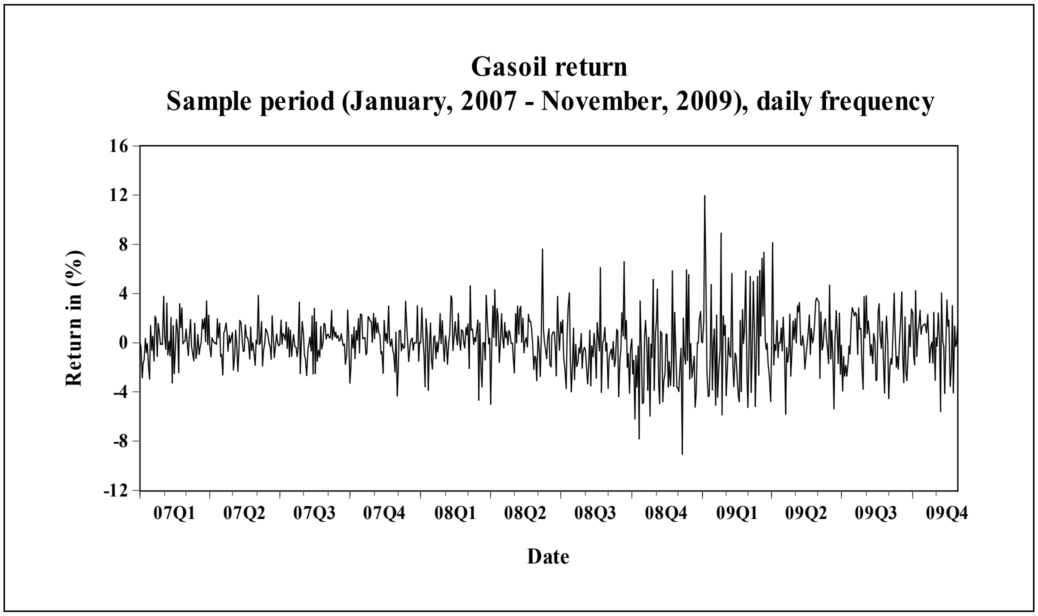


Figure A. 3 : The Volatility of gasoil return.

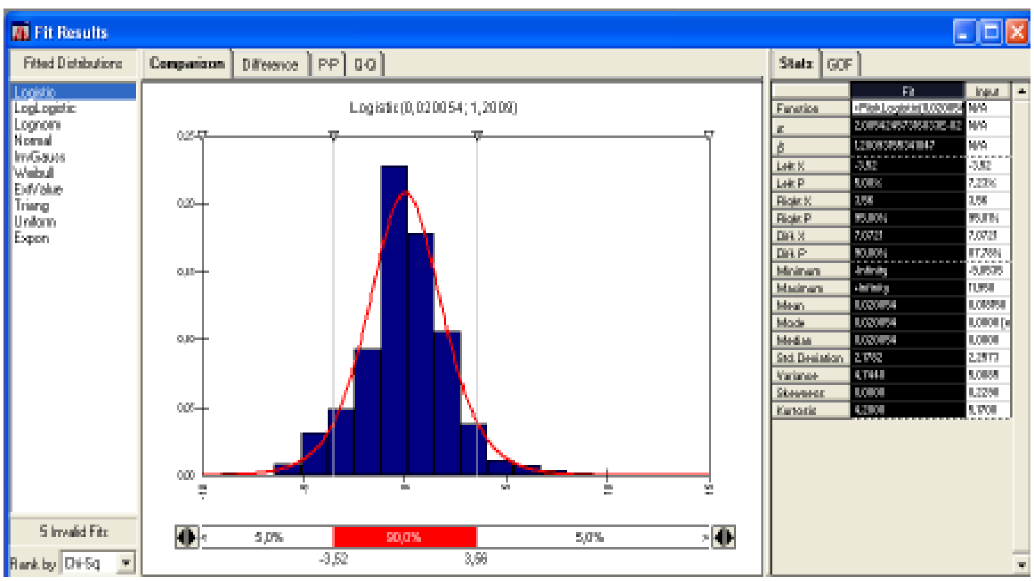


Figure A. 4 : Gasoil return distribution.

Gasoline

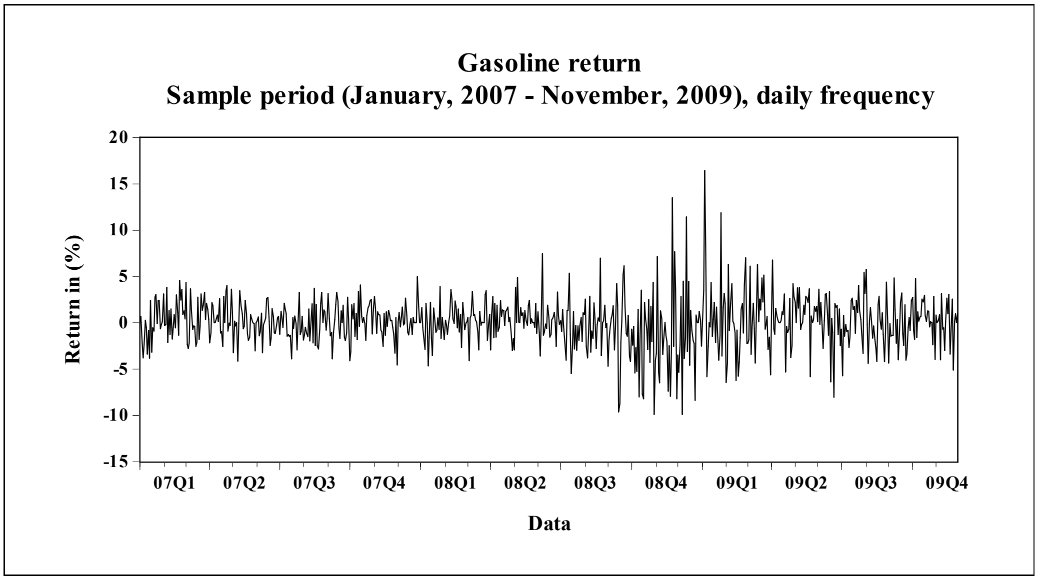


Figure A. 5 : The Volatility of gasoline return.

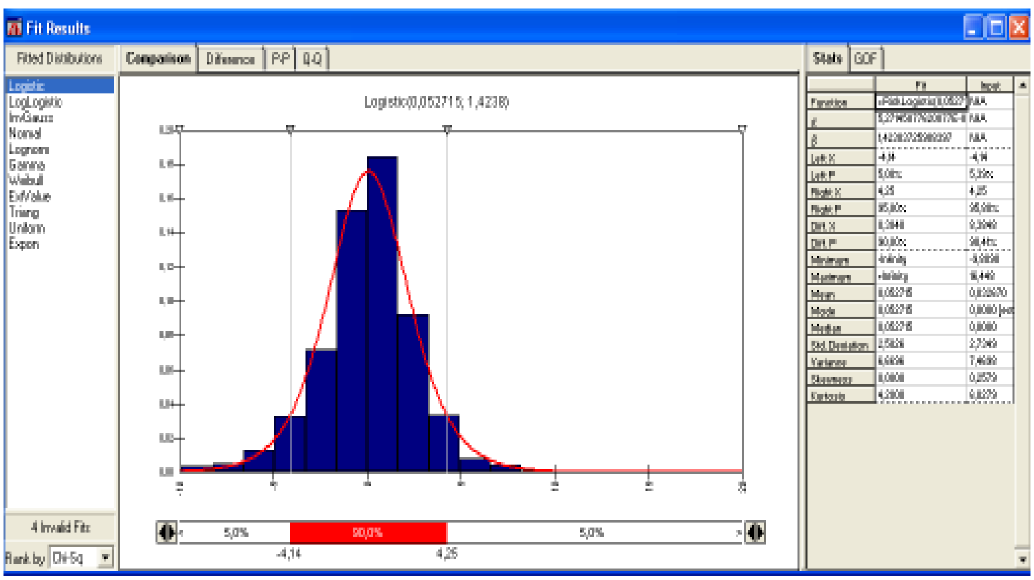


Figure A. 6 : Gasoline return distribution.

Fuel oil

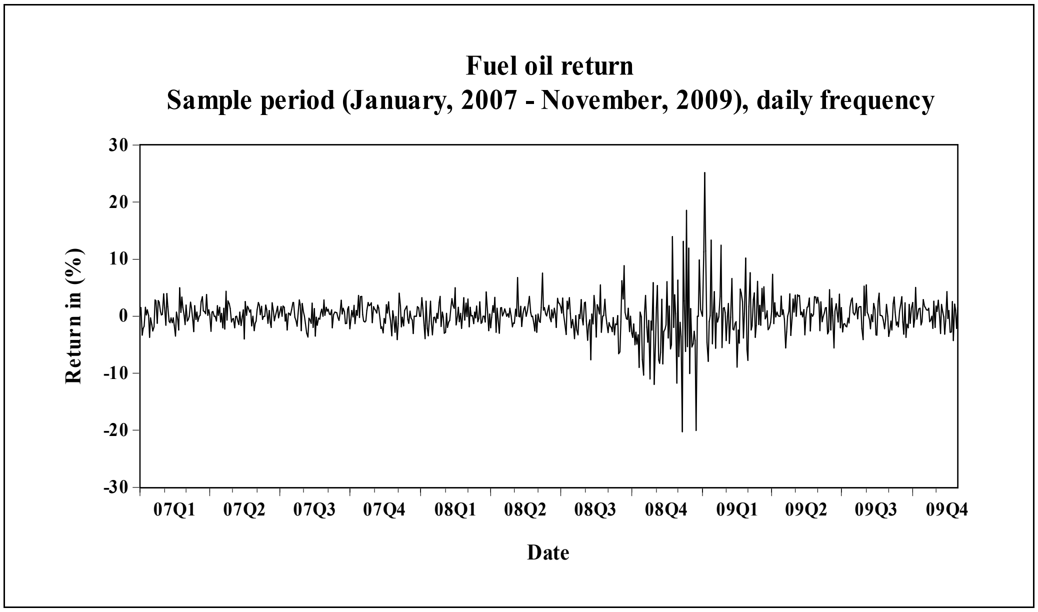


Figure A. 7 : The Volatility of fuel oil return.

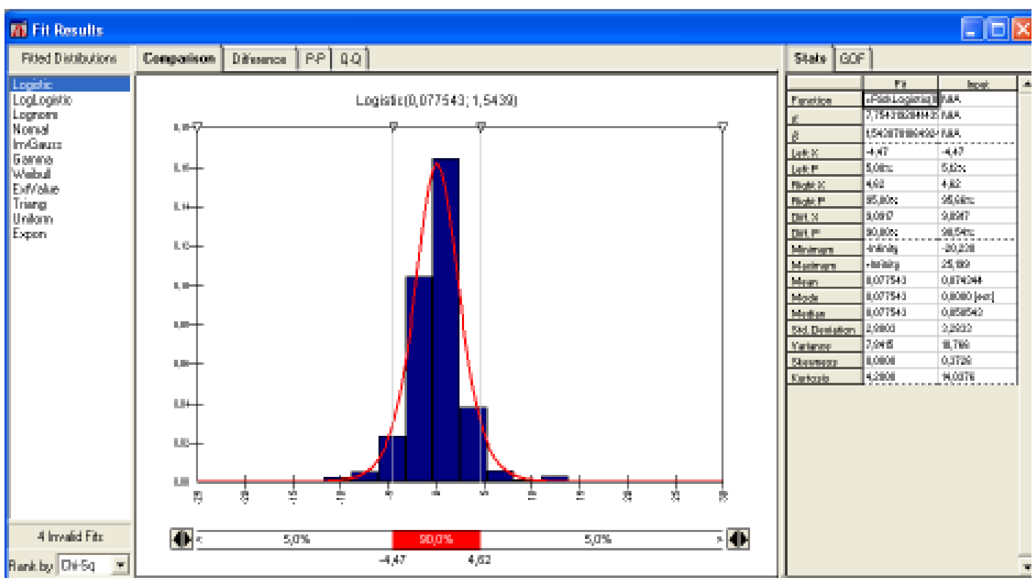


Figure A. 8 : Fuel oil return distribution.

Jet

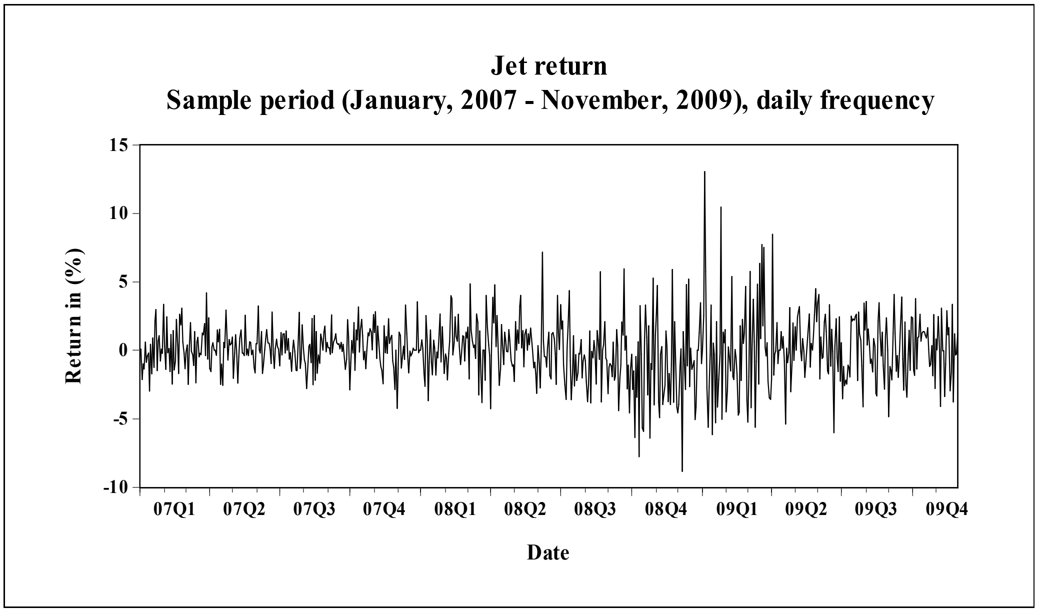


Figure A. 9 : The Volatility of jet return.

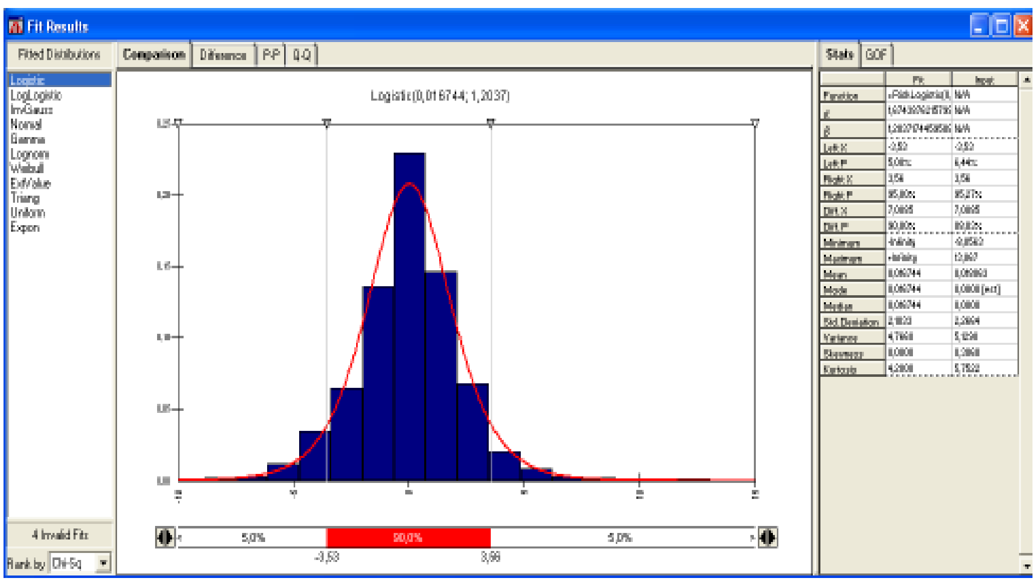


Figure A. 10 : Jet return distribution.

Ice Brent Futures

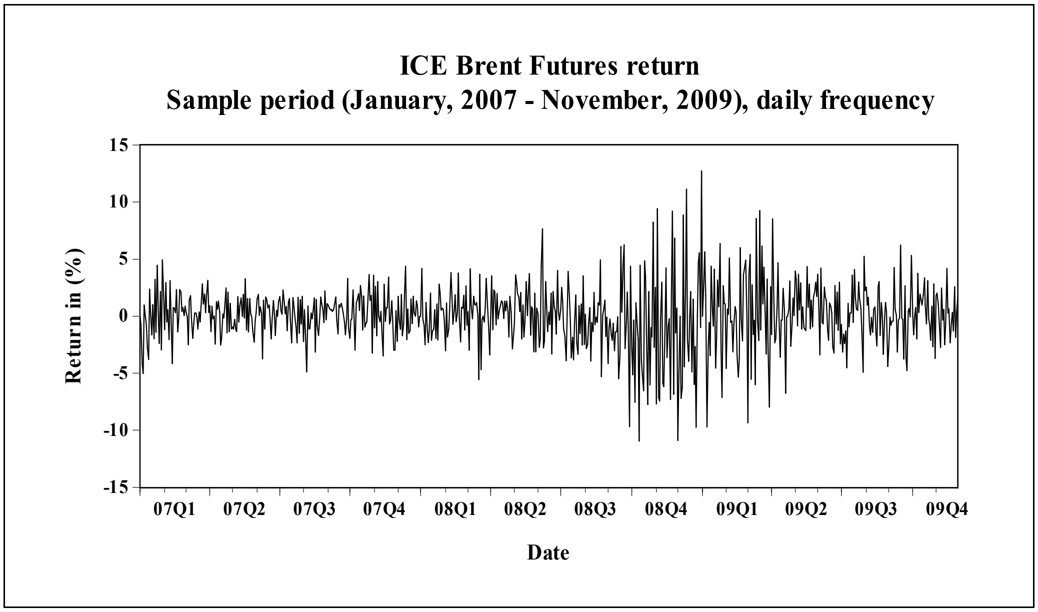


Figure A. 11: The Volatility of ICE Brent futures return.

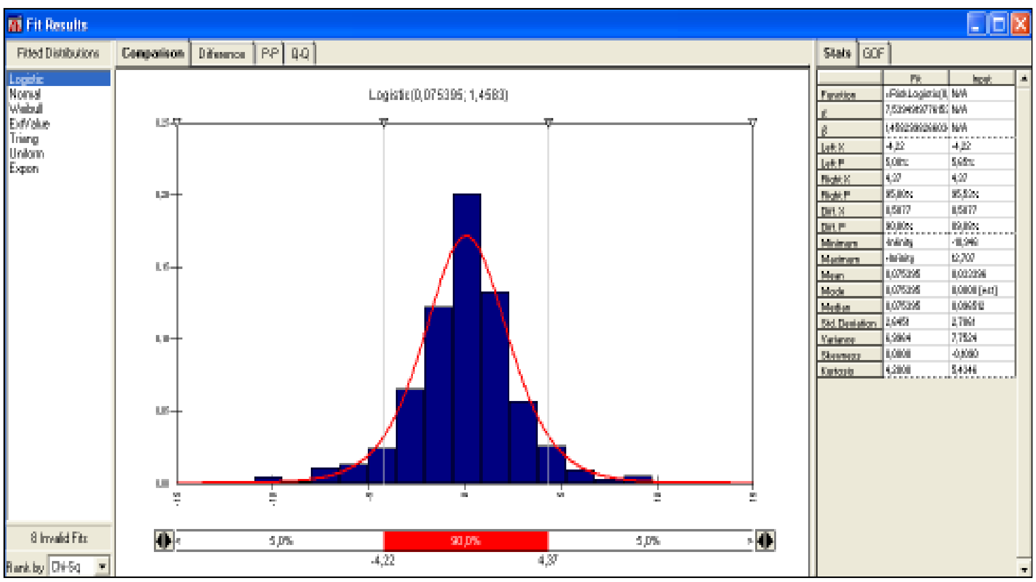


Figure A. 12 : ICE Brent futures return distribution.

Ice Gasoil Futures

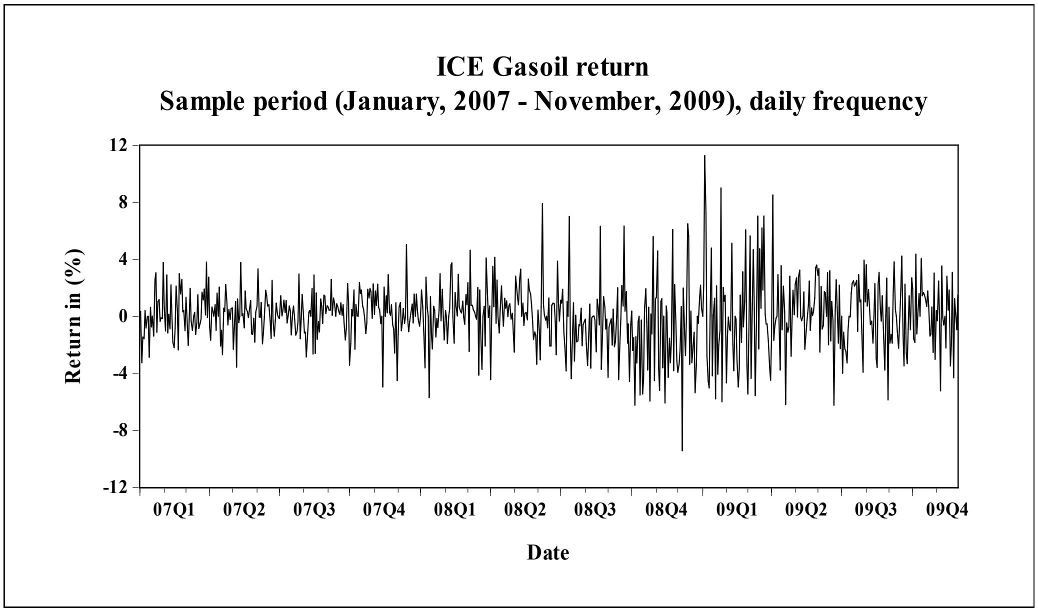


Figure A. 13 : The Volatility of ICE gasoil return.

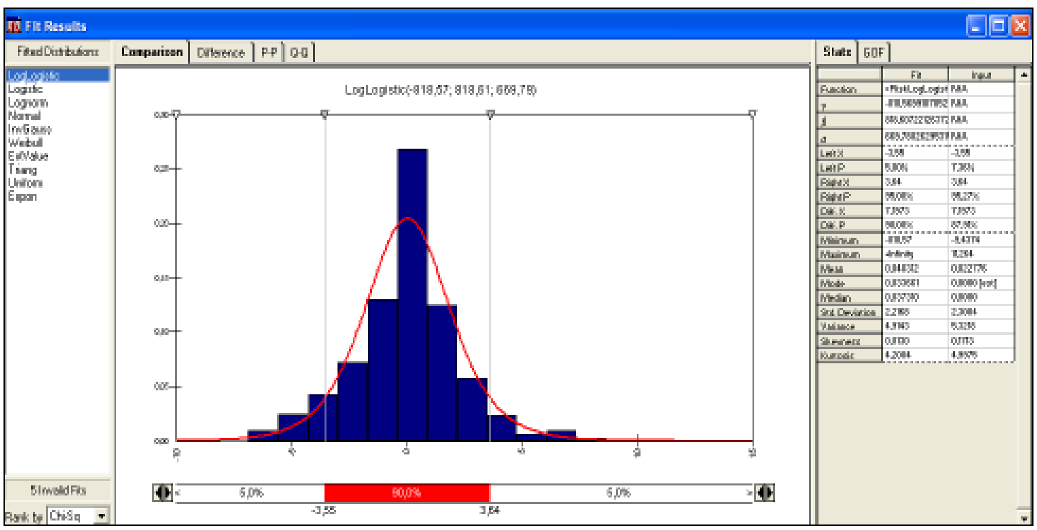


Figure A. 14 : ICE Gasoil return distribution.

APPENDIX B : The Volatility Modeling of Principal Components

- **Volatility Modeling of Principal Component 1 (PC1)**

Table B. 1 : The Correlogram and statistics of PC1.

Correlogram of PC1

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.057	0.057	2.4881	0.115
		2	0.023	0.020	2.8952	0.235
		3	0.021	0.019	3.2388	0.356
		4	0.068	0.066	6.8197	0.146
		5	0.004	-0.004	6.8346	0.233
		6	-0.031	-0.034	7.5607	0.272
		7	-0.014	-0.013	7.7059	0.359
		8	0.009	0.007	7.7619	0.457
		9	-0.067	-0.067	11.255	0.259
		10	0.065	0.078	14.490	0.152
		11	0.041	0.038	15.792	0.149
		12	-0.012	-0.020	15.901	0.196
		13	0.062	0.069	18.855	0.128
		14	0.085	0.070	24.520	0.040
		15	0.066	0.046	27.937	0.022
		16	0.048	0.043	29.700	0.020
		17	-0.002	-0.014	29.704	0.029
		18	0.057	0.039	32.274	0.020
		19	0.027	0.027	32.858	0.025
		20	0.034	0.032	33.758	0.028
		21	-0.007	-0.014	33.791	0.038
		22	-0.074	-0.071	38.150	0.018
		23	-0.022	-0.016	38.515	0.022
		24	0.022	0.017	38.901	0.028
		25	0.037	0.038	39.955	0.029
		26	0.010	0.006	40.031	0.039
		27	-0.019	-0.023	40.308	0.048
		28	0.050	0.032	42.321	0.040
		29	0.090	0.066	48.722	0.012
		30	0.032	0.012	49.543	0.014
		31	0.009	-0.011	49.602	0.018
		32	-0.023	-0.034	50.038	0.022
		33	-0.010	-0.023	50.114	0.029
		34	0.044	0.039	51.639	0.027
		35	0.008	0.013	51.688	0.034
		36	-0.032	-0.027	52.494	0.037

Table B. 2 : Mean equation of PC1.

Dependent Variable: PC1
Method: Least Squares
Date: 07/16/10 Time: 00:47
Sample (adjusted): 1/05/2007 11/30/2009
Included observations: 757 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.008238	0.092098	0.089451	0.9287
AR(4)	0.068398	0.036256	1.886538	0.0596

R-squared	0.004692	Mean dependent var	0.007479
Adjusted R-squared	0.003374	S.D. dependent var	2.364601
S.E. of regression	2.360610	Akaike info criterion	4.558355
Sum squared resid	4207.221	Schwarz criterion	4.570586
Log likelihood	-1723.337	Hannan-Quinn criter.	4.563066
F-statistic	3.559025	Durbin-Watson stat	1.892350
Prob(F-statistic)	0.059606		

Inverted AR Roots	.51	.00+.51i	-.00-.51i	-.51

Table B. 3 : Correlogram and statistics of PC1 residuals.

Correlogram of Residuals
Sample: 1/05/2007 11/30/2009
Included observations: 757
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.053	0.053	2.1497	
		2	0.023	0.020	2.5496	0.110
		3	0.018	0.016	2.8081	0.246
		4	-0.001	-0.003	2.8089	0.422
		5	0.004	0.004	2.8212	0.588
		6	-0.039	-0.040	4.0102	0.548
		7	-0.019	-0.015	4.2960	0.637
		8	0.004	0.008	4.3108	0.743
		9	-0.074	-0.073	8.5088	0.385
		10	0.061	0.070	11.382	0.250
		11	0.039	0.035	12.537	0.251
		12	-0.012	-0.018	12.655	0.316
		13	0.069	0.066	16.306	0.178
		14	0.079	0.073	21.114	0.071
		15	0.064	0.049	24.308	0.042
		16	0.047	0.040	26.026	0.038
		17	-0.007	-0.009	26.063	0.053
		18	0.057	0.049	28.606	0.038
		19	0.027	0.035	29.176	0.046
		20	0.032	0.037	29.976	0.052
		21	-0.009	-0.017	30.041	0.069
		22	-0.079	-0.067	34.887	0.029
		23	-0.021	-0.012	35.230	0.037
		24	0.016	0.017	35.425	0.047
		25	0.030	0.031	36.153	0.053
		26	0.013	-0.000	36.286	0.067
		27	-0.019	-0.024	36.560	0.082
		28	0.050	0.033	38.502	0.070
		29	0.089	0.070	44.719	0.024
		30	0.027	0.008	45.308	0.027
		31	0.010	-0.013	45.392	0.035
		32	-0.023	-0.029	45.810	0.042
		33	-0.021	-0.026	46.166	0.050
		34	0.040	0.038	47.455	0.049
		35	0.008	0.014	47.500	0.062

Table B. 4 : Correlogram of PC1 residuals squared.

Correlogram of Residuals Squared

Sample: 1/05/2007 11/30/2009
Included observations: 757
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.156	0.156	18.601	
		2	0.106	0.083	27.086	0.000
		3	0.109	0.083	36.111	0.000
		4	0.208	0.180	69.155	0.000
		5	0.132	0.071	82.529	0.000
		6	0.130	0.074	95.373	0.000
		7	0.082	0.017	100.49	0.000
		8	0.121	0.054	111.75	0.000
		9	0.263	0.209	164.90	0.000
		10	0.177	0.085	188.93	0.000
		11	0.073	-0.013	193.00	0.000
		12	0.165	0.097	213.88	0.000
		13	0.152	0.032	231.64	0.000
		14	0.133	0.029	245.38	0.000
		15	0.248	0.185	293.05	0.000
		16	0.143	0.036	308.84	0.000
		17	0.219	0.143	346.11	0.000
		18	0.119	-0.021	357.04	0.000
		19	0.059	-0.102	359.79	0.000
		20	0.108	0.034	368.95	0.000
		21	0.309	0.211	443.37	0.000
		22	0.154	0.038	461.97	0.000
		23	0.153	0.085	480.35	0.000
		24	0.132	-0.020	493.96	0.000
		25	0.158	-0.019	513.46	0.000
		26	0.104	-0.041	521.91	0.000
		27	0.197	0.083	552.51	0.000
		28	0.098	0.050	560.16	0.000
		29	0.063	-0.051	563.26	0.000
		30	0.234	0.061	606.59	0.000
		31	0.175	0.011	630.96	0.000
		32	0.200	0.080	662.65	0.000
		33	0.129	0.019	675.78	0.000
		34	0.080	-0.043	680.89	0.000
		35	0.065	-0.053	684.20	0.000

Table B. 5 : Heteroskedasticity test of PC1.

Heteroskedasticity Test: ARCH

F-statistic	12.00731	Prob. F(5,750)	0.0000
Obs*R-squared	56.03160	Prob. Chi-Square(5)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/16/10 Time: 00:57
Sample (adjusted): 1/08/2007 11/30/2009
Included observations: 756 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.004645	0.571184	5.260383	0.0000
RESID^2(-1)	0.108308	0.036423	2.973618	0.0030
RESID^2(-2)	0.054225	0.036094	1.502350	0.1334
RESID^2(-3)	0.054914	0.036088	1.521665	0.1285
RESID^2(-4)	0.171314	0.036088	4.747145	0.0000
RESID^2(-5)	0.071893	0.036435	1.973178	0.0488

R-squared	0.074116	Mean dependent var	5.561425
Adjusted R-squared	0.067943	S.D. dependent var	12.85159
S.E. of regression	12.40732	Akaike info criterion	7.882356
Sum squared resid	115456.3	Schwarz criterion	7.919086
Log likelihood	-2973.531	Hannan-Quinn criter.	7.896504
F-statistic	12.00731	Durbin-Watson stat	2.010458
Prob(F-statistic)	0.000000		

Table B. 6 : The Volatility and mean equation modelling of PC1.

Dependent Variable: PC1
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/16/10 Time: 00:58
Sample (adjusted): 1/05/2007 11/30/2009
Included observations: 757 after adjustments
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.143455	0.067735	2.117881	0.0342
AR(4)	0.057773	0.034594	1.670032	0.0949
		Variance Equation		
C	0.018310	0.012872	1.422403	0.1549
RESID(-1)^2	0.039379	0.010839	3.633232	0.0003
GARCH(-1)	0.958242	0.011479	83.48105	0.0000

R-squared	0.001666	Mean dependent var	0.007479
Adjusted R-squared	-0.003644	S.D. dependent var	2.364601
S.E. of regression	2.368906	Akaike info criterion	4.287074
Sum squared resid	4220.009	Schwarz criterion	4.317651
Log likelihood	-1617.658	Hannan-Quinn criter.	4.298851
F-statistic	0.313795	Durbin-Watson stat	1.886496
Prob(F-statistic)	0.868829		

Inverted AR Roots	.49	.00+.49i	-.00-.49i	-.49

Table B. 7 : Correlogram of PC1 standardized residuals squared.

Correlogram of Standardized Residuals Squared

Sample: 1/05/2007 11/30/2009
Included observations: 757
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.036	-0.036	0.9918	
		2	-0.008	-0.010	1.0461	0.306
		3	-0.027	-0.028	1.6023	0.449
		4	0.026	0.024	2.1055	0.551
		5	0.003	0.004	2.1123	0.715
		6	-0.064	-0.064	5.2351	0.388
		7	-0.013	-0.017	5.3715	0.497
		8	0.012	0.010	5.4854	0.601
		9	-0.001	-0.005	5.4870	0.704
		10	0.017	0.019	5.6968	0.770
		11	-0.030	-0.028	6.4060	0.780
		12	0.007	0.000	6.4396	0.842
		13	0.015	0.014	6.6160	0.882
		14	0.006	0.006	6.6473	0.919
		15	0.008	0.010	6.6968	0.946
		16	-0.054	-0.051	8.9760	0.879
		17	0.050	0.043	10.927	0.814
		18	-0.026	-0.025	11.462	0.832
		19	-0.037	-0.039	12.542	0.818
		20	-0.040	-0.038	13.815	0.794
		21	0.067	0.063	17.307	0.633
		22	0.044	0.041	18.847	0.595
		23	0.025	0.033	19.340	0.624
		24	-0.032	-0.025	20.124	0.634
		25	0.056	0.048	22.625	0.542
		26	0.002	0.002	22.628	0.599
		27	0.082	0.085	27.862	0.365
		28	-0.006	0.015	27.887	0.417
		29	-0.021	-0.017	28.222	0.453
		30	0.009	0.007	28.283	0.503
		31	-0.007	-0.007	28.318	0.554
		32	0.076	0.079	32.852	0.376

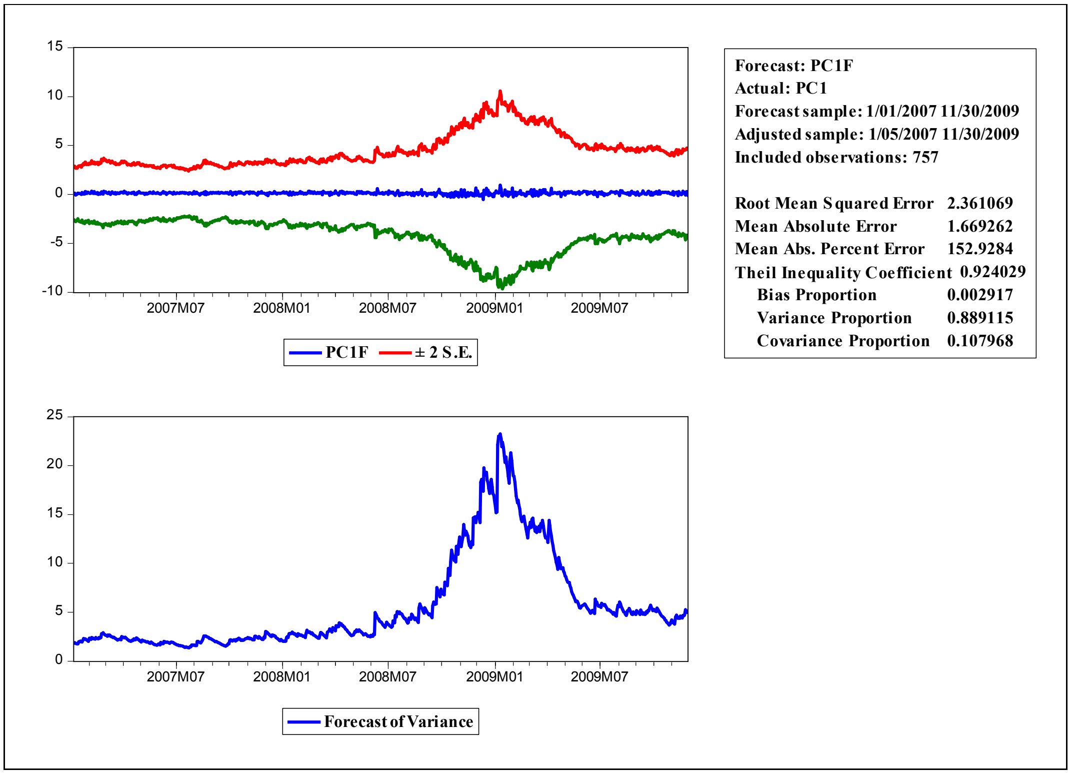


Figure B. 1 : Forecast of PC1 variance.

b

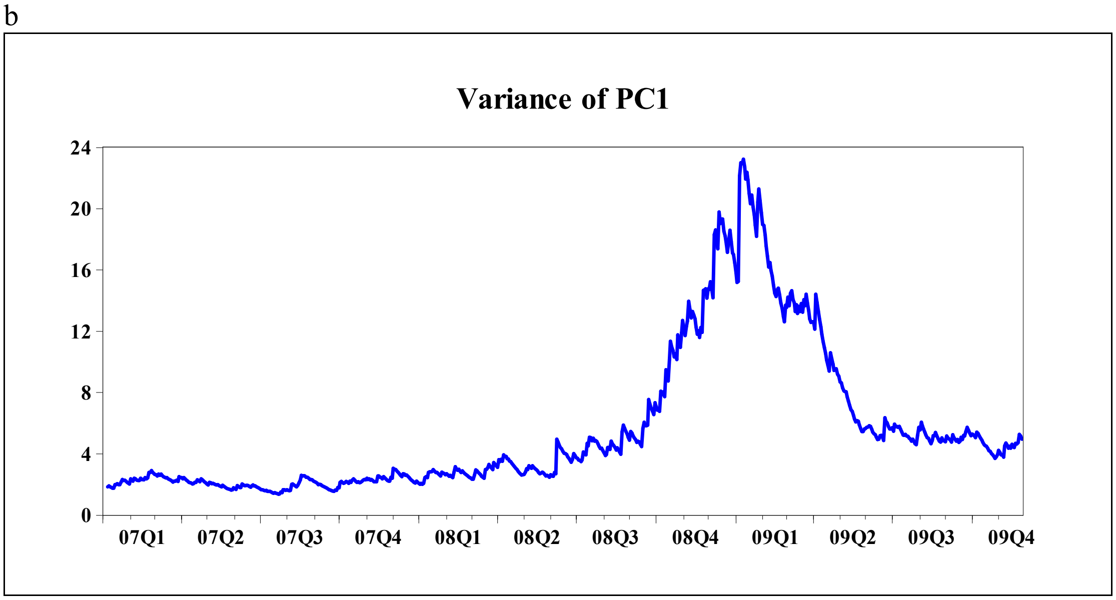


Figure B. 2 : The variance of PC1.

- **Volatility Modeling of Principal Component 2 (PC2)**

Table B. 8 : The Correlogram and statistics of PC2.

Correlogram of PC2

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.304	-0.304	70.416	0.000
		2	-0.089	-0.200	76.518	0.000
		3	0.034	-0.068	77.381	0.000
		4	-0.030	-0.067	78.055	0.000
		5	-0.050	-0.095	79.982	0.000
		6	-0.044	-0.123	81.464	0.000
		7	0.003	-0.092	81.469	0.000
		8	-0.031	-0.107	82.191	0.000
		9	-0.043	-0.138	83.642	0.000
		10	0.153	0.061	101.64	0.000
		11	-0.085	-0.058	107.19	0.000
		12	-0.030	-0.081	107.88	0.000
		13	-0.020	-0.122	108.18	0.000
		14	0.022	-0.075	108.57	0.000
		15	0.115	0.089	118.85	0.000
		16	0.030	0.126	119.57	0.000
		17	0.053	0.171	121.78	0.000
		18	-0.097	0.016	129.09	0.000
		19	-0.086	-0.098	134.93	0.000
		20	0.116	0.048	145.51	0.000
		21	-0.101	-0.014	153.51	0.000
		22	-0.093	-0.090	160.30	0.000
		23	0.068	-0.006	163.89	0.000
		24	-0.013	-0.050	164.01	0.000
		25	0.096	0.051	171.35	0.000
		26	-0.043	-0.021	172.79	0.000
		27	0.036	0.012	173.81	0.000
		28	-0.029	0.011	174.48	0.000
		29	-0.042	-0.032	175.86	0.000
		30	0.125	0.058	188.35	0.000
		31	-0.029	0.020	189.02	0.000
		32	0.022	0.066	189.42	0.000
		33	-0.103	-0.085	197.89	0.000
		34	0.036	0.006	198.93	0.000
		35	0.033	0.032	199.79	0.000
		36	-0.100	-0.026	207.75	0.000

Table B. 9 : Mean equation of PC2.

Dependent Variable: PC2
Method: Least Squares
Date: 07/16/10 Time: 02:07
Sample (adjusted): 1/03/2007 11/30/2009
Included observations: 759 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000183	0.016097	0.011339	0.9910
AR(1)	-0.364341	0.035632	-10.22522	0.0000
AR(2)	-0.199982	0.035634	-5.612134	0.0000

R-squared	0.128507	Mean dependent var	0.000453
Adjusted R-squared	0.126201	S.D. dependent var	0.742139
S.E. of regression	0.693730	Akaike info criterion	2.110478
Sum squared resid	363.8340	Schwarz criterion	2.128786
Log likelihood	-797.9265	Hannan-Quinn criter.	2.117529
F-statistic	55.73842	Durbin-Watson stat	2.027173
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.18+.41i	-.18-.41i

Table B. 10 : Correlogram of PC2 residuals.

Correlogram of Residuals

Sample: 1/03/2007 11/30/2009
Included observations: 759
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.014	-0.014	0.1573	
		2	-0.034	-0.035	1.0565	
		3	-0.095	-0.096	7.9986	0.005
		4	-0.079	-0.084	12.774	0.002
		5	-0.096	-0.108	19.861	0.000
		6	-0.097	-0.122	27.115	0.000
		7	-0.056	-0.095	29.561	0.000
		8	-0.035	-0.088	30.530	0.000
		9	-0.016	-0.079	30.718	0.000
		10	0.127	0.068	43.245	0.000
		11	-0.067	-0.122	46.682	0.000
		12	-0.053	-0.110	48.818	0.000
		13	-0.023	-0.069	49.225	0.000
		14	0.077	0.026	53.803	0.000
		15	0.190	0.171	81.882	0.000
		16	0.108	0.125	91.006	0.000
		17	0.044	0.080	92.507	0.000
		18	-0.113	-0.063	102.42	0.000
		19	-0.118	-0.077	113.35	0.000
		20	0.020	0.066	113.66	0.000
		21	-0.129	-0.055	126.64	0.000
		22	-0.118	-0.094	137.61	0.000
		23	0.038	0.032	138.74	0.000
		24	0.034	-0.030	139.62	0.000
		25	0.126	0.049	152.14	0.000
		26	-0.001	-0.028	152.14	0.000
		27	0.026	0.012	152.68	0.000
		28	-0.023	0.013	153.09	0.000
		29	-0.007	-0.015	153.13	0.000
		30	0.132	0.081	166.86	0.000
		31	0.002	0.001	166.86	0.000
		32	0.001	0.022	166.87	0.000
		33	-0.108	-0.083	176.20	0.000
		34	-0.005	0.039	176.22	0.000
		35	-0.008	0.024	176.27	0.000

Table B. 11 : Correlogram and statistics of PC2 squared residuals.

Correlogram of Residuals Squared

Sample: 1/03/2007 11/30/2009
Included observations: 759
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.254	0.254	49.127	
		2	0.254	0.203	98.473	
		3	0.234	0.146	140.44	0.000
		4	0.158	0.041	159.43	0.000
		5	0.320	0.238	237.74	0.000
		6	0.055	-0.121	240.05	0.000
		7	0.198	0.110	270.25	0.000
		8	0.147	0.021	286.76	0.000
		9	0.140	0.057	301.74	0.000
		10	0.182	0.030	327.22	0.000
		11	0.102	0.043	335.21	0.000
		12	0.344	0.244	426.64	0.000
		13	0.177	0.018	450.97	0.000
		14	0.259	0.127	502.78	0.000
		15	0.223	0.030	541.22	0.000
		16	0.149	0.011	558.41	0.000
		17	0.360	0.167	659.28	0.000
		18	0.216	0.099	695.55	0.000
		19	0.265	0.056	750.17	0.000
		20	0.136	-0.068	764.64	0.000
		21	0.145	0.021	781.04	0.000
		22	0.223	0.019	819.92	0.000
		23	0.219	0.160	857.46	0.000
		24	0.148	-0.115	874.57	0.000
		25	0.150	0.061	892.39	0.000
		26	0.164	-0.048	913.49	0.000
		27	0.116	-0.050	924.06	0.000
		28	0.131	-0.008	937.52	0.000
		29	0.111	-0.076	947.26	0.000
		30	0.125	-0.036	959.65	0.000
		31	0.176	-0.014	984.23	0.000
		32	0.129	0.021	997.46	0.000
		33	0.173	0.029	1021.3	0.000
		34	0.117	-0.060	1032.1	0.000

Table B. 12 : Heteroskedasticity test of PC2.

Heteroskedasticity Test: ARCH

F-statistic	31.64880	Prob. F(5,750)	0.0000
Obs*R-squared	131.7184	Prob. Chi-Square(5)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/16/10 Time: 02:09
Sample (adjusted): 1/08/2007 11/30/2009
Included observations: 756 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.175546	0.048625	3.610201	0.0003
RESID^2(-1)	0.157469	0.035455	4.441431	0.0000
RESID^2(-2)	0.132932	0.035868	3.706191	0.0002
RESID^2(-3)	0.099953	0.036012	2.775516	0.0056
RESID^2(-4)	0.001416	0.035864	0.039478	0.9685
RESID^2(-5)	0.238527	0.035398	6.738400	0.0000

R-squared	0.174231	Mean dependent var	0.477814
Adjusted R-squared	0.168726	S.D. dependent var	1.250010
S.E. of regression	1.139687	Akaike info criterion	3.107290
Sum squared resid	974.1652	Schwarz criterion	3.144020
Log likelihood	-1168.555	Hannan-Quinn criter.	3.121437
F-statistic	31.64880	Durbin-Watson stat	1.941952
Prob(F-statistic)	0.000000		

Table B. 13 : The Volatility and mean equation modeling of PC2.

Dependent Variable: PC2
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/16/10 Time: 02:10
Sample (adjusted): 1/03/2007 11/30/2009
Included observations: 759 after adjustments
Convergence achieved after 12 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005714	0.010054	0.568298	0.5698
AR(1)	-0.440532	0.038025	-11.58532	0.0000
AR(2)	-0.235007	0.038133	-6.162792	0.0000
		Variance Equation		
C	0.006587	0.002665	2.471275	0.0135
RESID(-1)^2	0.082648	0.019133	4.319678	0.0000
GARCH(-1)	0.898029	0.022328	40.21955	0.0000

R-squared	0.122937	Mean dependent var	0.000453
Adjusted R-squared	0.117113	S.D. dependent var	0.742139
S.E. of regression	0.697329	Akaike info criterion	1.736699
Sum squared resid	366.1594	Schwarz criterion	1.773315
Log likelihood	-653.0772	Hannan-Quinn criter.	1.750800
F-statistic	21.10945	Durbin-Watson stat	1.879212
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.22+.43i	-.22-.43i

Table B. 14 : Correlogram and statistics of PC2 standardized residuals squared.

Correlogram of Standardized Residuals Squared

Sample: 1/03/2007 11/30/2009
Included observations: 759
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.048	-0.048	1.7347	
		2	0.019	0.017	2.0094	
		3	-0.001	0.001	2.0097	0.156
		4	0.014	0.014	2.1650	0.339
		5	0.011	0.012	2.2542	0.521
		6	-0.052	-0.051	4.3046	0.366
		7	0.034	0.029	5.2108	0.391
		8	0.018	0.023	5.4655	0.486
		9	0.034	0.035	6.3665	0.498
		10	-0.012	-0.008	6.4728	0.594
		11	-0.044	-0.047	7.9810	0.536
		12	0.060	0.053	10.768	0.376
		13	-0.061	-0.053	13.694	0.250
		14	0.008	0.002	13.750	0.317
		15	-0.000	0.006	13.750	0.392
		16	0.019	0.015	14.032	0.447
		17	0.031	0.028	14.758	0.469
		18	0.008	0.018	14.811	0.539
		19	0.005	-0.001	14.834	0.607
		20	-0.043	-0.040	16.251	0.575
		21	0.006	-0.001	16.282	0.638
		22	0.023	0.029	16.700	0.672
		23	0.057	0.065	19.285	0.567
		24	-0.019	-0.023	19.564	0.610
		25	0.046	0.047	21.206	0.568
		26	-0.023	-0.030	21.634	0.601
		27	-0.026	-0.029	22.162	0.626
		28	-0.023	-0.020	22.593	0.656
		29	-0.036	-0.032	23.613	0.652
		30	-0.006	-0.014	23.643	0.700
		31	0.034	0.035	24.553	0.701
		32	0.028	0.030	25.162	0.717
		33	0.009	0.008	25.224	0.758
		34	-0.010	-0.012	25.298	0.794
		35	0.019	0.012	25.577	0.818

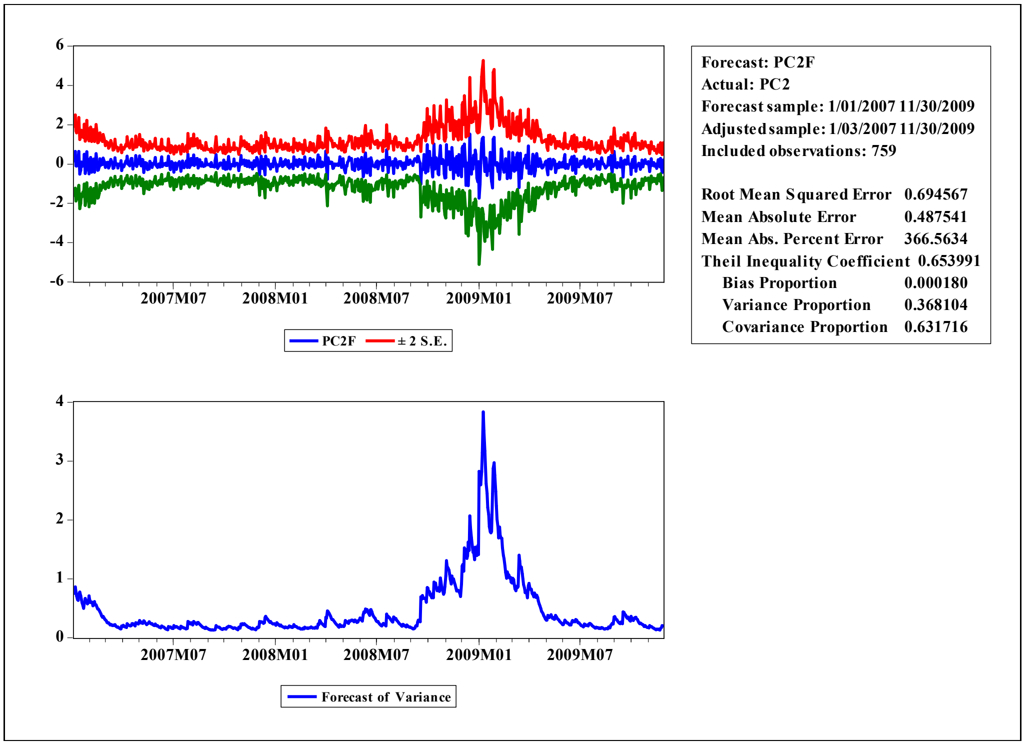


Figure B. 3 : Forecast of PC2 variance.

- **Volatility Modeling of Principal Component 3 (PC3)**

Table B. 15 : Correlogram and statistics of PC3.

Correlogram of PC3

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.020	-0.020	0.2966	0.586
		2	0.057	0.057	2.8093	0.245
		3	0.029	0.031	3.4448	0.328
		4	-0.036	-0.038	4.4310	0.351
		5	0.112	0.107	14.014	0.016
		6	0.058	0.067	16.645	0.011
		7	-0.013	-0.022	16.776	0.019
		8	0.079	0.066	21.643	0.006
		9	-0.134	-0.128	35.595	0.000
		10	0.150	0.136	52.922	0.000
		11	-0.087	-0.095	58.814	0.000
		12	0.032	0.033	59.624	0.000
		13	0.009	-0.014	59.686	0.000
		14	-0.071	-0.044	63.621	0.000
		15	0.047	0.033	65.317	0.000
		16	-0.007	-0.014	65.361	0.000
		17	-0.019	0.012	65.643	0.000
		18	0.051	0.003	67.687	0.000
		19	-0.053	0.012	69.856	0.000
		20	0.036	-0.013	70.870	0.000
		21	-0.046	-0.020	72.508	0.000
		22	-0.032	-0.038	73.337	0.000
		23	0.023	0.007	73.737	0.000
		24	0.016	0.049	73.942	0.000
		25	0.063	0.043	77.049	0.000
		26	-0.021	-0.017	77.382	0.000
		27	0.024	0.041	77.837	0.000
		28	-0.009	-0.029	77.906	0.000
		29	-0.012	0.004	78.020	0.000
		30	-0.044	-0.081	79.537	0.000
		31	-0.009	-0.004	79.608	0.000
		32	0.014	0.022	79.768	0.000
		33	0.076	0.073	84.364	0.000
		34	0.074	0.096	88.793	0.000
		35	0.044	0.024	90.323	0.000
		36	0.008	0.034	90.373	0.000

Table B. 16 : Mean equation of PC3.

Dependent Variable: PC3
Method: Least Squares
Date: 07/20/10 Time: 00:33
Sample (adjusted): 1/12/2007 11/30/2009
Included observations: 752 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000529	0.019777	-0.026737	0.9787
AR(6)	0.062672	0.036155	1.733407	0.0834
AR(9)	-0.136634	0.036161	-3.778525	0.0002

R-squared	0.022083	Mean dependent var	-0.000568
Adjusted R-squared	0.019472	S.D. dependent var	0.588193
S.E. of regression	0.582438	Akaike info criterion	1.760794
Sum squared resid	254.0866	Schwarz criterion	1.779236
Log likelihood	-659.0587	Hannan-Quinn criter.	1.767900
F-statistic	8.456769	Durbin-Watson stat	1.989488
Prob(F-statistic)	0.000233		

Inverted AR Roots	.75-.25i	.75+.25i	.41+.71i	.41-.71i
	-.16+.78i	-.16-.78i	-.59+.52i	-.59-.52i
	-.82			

Table B. 17 : Correlogram and statistics of PC3 residuals.

Correlogram of Residuals

Sample: 1/12/2007 11/30/2009
Included observations: 752
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.005	0.005	0.0196	
		2	0.043	0.043	1.4434	
		3	0.041	0.041	2.7331	0.098
		4	-0.034	-0.036	3.6166	0.164
		5	0.107	0.105	12.369	0.006
		6	0.008	0.008	12.421	0.014
		7	-0.007	-0.013	12.458	0.029
		8	0.077	0.068	16.986	0.009
		9	-0.001	0.006	16.987	0.017
		10	0.151	0.138	34.429	0.000
		11	-0.084	-0.097	39.804	0.000
		12	0.024	0.024	40.258	0.000
		13	0.003	-0.017	40.264	0.000
		14	-0.061	-0.050	43.125	0.000
		15	0.070	0.041	46.944	0.000
		16	-0.008	0.004	46.996	0.000
		17	-0.008	-0.006	47.044	0.000
		18	0.034	0.004	47.939	0.000
		19	-0.040	-0.015	49.206	0.000
		20	0.030	-0.001	49.904	0.000
		21	-0.054	-0.034	52.158	0.000
		22	-0.033	-0.034	53.023	0.000
		23	0.019	0.017	53.299	0.000
		24	0.033	0.058	54.135	0.000
		25	0.080	0.056	59.114	0.000
		26	-0.023	-0.017	59.541	0.000
		27	0.033	0.039	60.372	0.000
		28	-0.015	-0.033	60.556	0.000
		29	-0.012	0.005	60.661	0.000
		30	-0.047	-0.074	62.427	0.000
		31	-0.020	0.003	62.738	0.000
		32	0.020	0.018	63.046	0.000
		33	0.079	0.067	67.925	0.000
		34	0.092	0.093	74.637	0.000

Table B. 18 : Correlogram and statistics of PC3 residual squared.

Correlogram of Residuals Squared

Sample: 1/12/2007 11/30/2009
Included observations: 752
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.236	0.236	42.174	
		2	0.063	0.008	45.206	
		3	0.296	0.296	111.46	0.000
		4	0.204	0.080	142.99	0.000
		5	0.214	0.177	177.73	0.000
		6	0.116	-0.041	187.90	0.000
		7	0.059	-0.021	190.51	0.000
		8	0.234	0.138	232.41	0.000
		9	0.239	0.129	275.89	0.000
		10	0.141	0.068	291.04	0.000
		11	0.122	0.005	302.40	0.000
		12	0.174	0.052	325.73	0.000
		13	0.158	-0.004	344.80	0.000
		14	0.087	-0.031	350.64	0.000
		15	0.115	0.039	360.82	0.000
		16	0.242	0.169	405.85	0.000
		17	0.220	0.096	443.03	0.000
		18	0.064	-0.074	446.24	0.000
		19	0.098	-0.026	453.60	0.000
		20	0.193	0.036	482.36	0.000
		21	0.207	0.093	515.74	0.000
		22	0.092	-0.013	522.39	0.000
		23	0.058	0.003	525.00	0.000
		24	0.137	-0.008	539.57	0.000
		25	0.154	-0.024	558.10	0.000
		26	0.156	0.055	577.11	0.000
		27	0.098	0.025	584.57	0.000
		28	0.050	-0.040	586.54	0.000
		29	0.247	0.141	634.49	0.000
		30	0.219	0.081	672.33	0.000
		31	0.089	0.015	678.51	0.000
		32	0.098	-0.074	686.14	0.000
		33	0.041	-0.150	687.49	0.000
		34	0.066	-0.046	690.93	0.000

Table B. 19 : Heteroskedasticity test of PC3.

Heteroskedasticity Test: ARCH

F-statistic	30.76807	Prob. F(5,746)	0.0000
Obs*R-squared	128.5650	Prob. Chi-Square(5)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/20/10 Time: 00:37
Sample: 1/12/2007 11/30/2009
Included observations: 752

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.136311	0.036665	3.717791	0.0002
RESID^2(-1)	0.194001	0.036035	5.383726	0.0000
RESID^2(-2)	-0.105271	0.036689	-2.869260	0.0042
RESID^2(-3)	0.287054	0.035361	8.117886	0.0000
RESID^2(-4)	0.043710	0.036688	1.191374	0.2339
RESID^2(-5)	0.176965	0.036029	4.911784	0.0000

R-squared	0.170964	Mean dependent var	0.337881
Adjusted R-squared	0.165408	S.D. dependent var	0.941809
S.E. of regression	0.860399	Akaike info criterion	2.545106
Sum squared resid	552.2539	Schwarz criterion	2.581990
Log likelihood	-950.9599	Hannan-Quinn criter.	2.559316
F-statistic	30.76807	Durbin-Watson stat	1.985544
Prob(F-statistic)	0.000000		

Table B. 20 : The Volatility and mean equation of PC3.

Dependent Variable: PC3
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/20/10 Time: 00:39
Sample (adjusted): 1/12/2007 11/30/2009
Included observations: 752 after adjustments
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-2)^2 + C(7)*GARCH(-1)
+ C(8)*GARCH(-2)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.009208	0.017291	-0.532535	0.5944
AR(6)	0.074292	0.038579	1.925704	0.0541
AR(9)	-0.062117	0.036095	-1.720895	0.0853
		Variance Equation		
C	0.003542	0.001829	1.936615	0.0528
RESID(-1)^2	0.147334	0.029234	5.039745	0.0000
RESID(-2)^2	-0.071391	0.032380	-2.204770	0.0275
GARCH(-1)	0.260464	0.128963	2.019677	0.0434
GARCH(-2)	0.652521	0.120701	5.406119	0.0000

R-squared	0.016137	Mean dependent var	-0.000568
Adjusted R-squared	0.006881	S.D. dependent var	0.588193
S.E. of regression	0.586166	Akaike info criterion	1.455165
Sum squared resid	255.6313	Schwarz criterion	1.504343
Log likelihood	-539.1420	Hannan-Quinn criter.	1.474112
F-statistic	1.743301	Durbin-Watson stat	2.025593
Prob(F-statistic)	0.095900		

Inverted AR Roots	.68+.21i	.68-.21i	.39+.67i	.39-.67i
	-.16+.70i	-.16-.70i	-.53-.49i	-.53+.49i
	-.77			

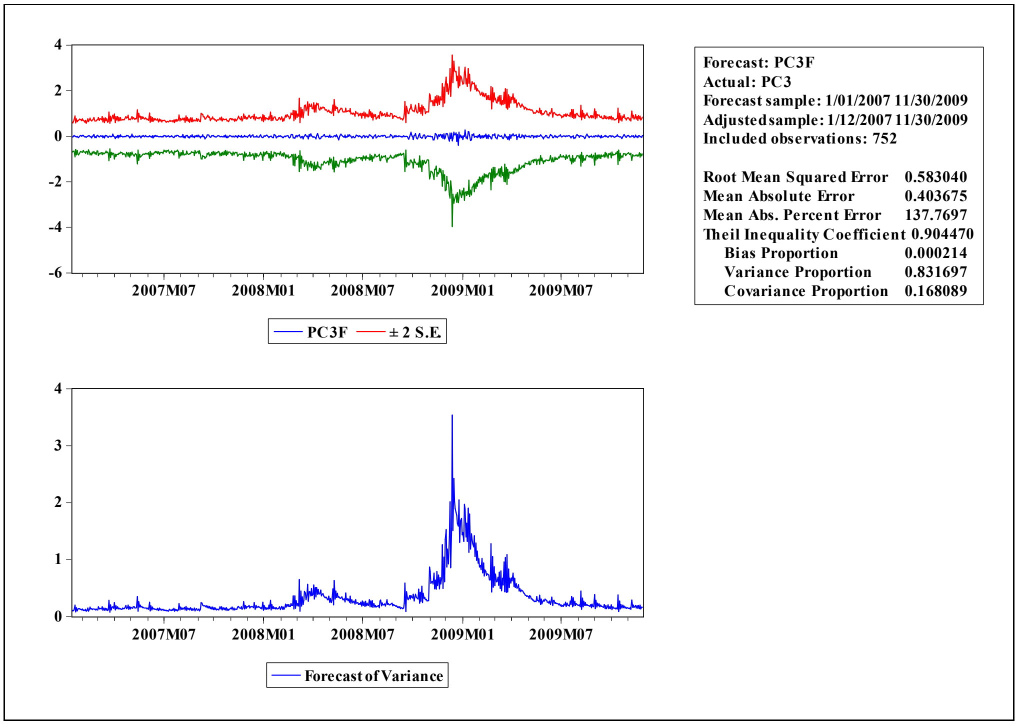


Figure B. 4 : Forecast of PC3 variance.

- **Volatility Modeling of Principal Component 4 (PC4)**

Table B. 21 : Correlogram and statistics of PC4.

Correlogram of PC4

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.047	0.047	1.7211	0.190
		2	-0.038	-0.041	2.8515	0.240
		3	-0.123	-0.120	14.515	0.002
		4	-0.029	-0.020	15.169	0.004
		5	-0.080	-0.088	20.027	0.001
		6	-0.006	-0.016	20.053	0.003
		7	-0.071	-0.085	23.941	0.001
		8	-0.046	-0.064	25.551	0.001
		9	-0.034	-0.046	26.430	0.002
		10	0.102	0.074	34.438	0.000
		11	-0.032	-0.065	35.214	0.000
		12	-0.003	-0.019	35.223	0.000
		13	-0.012	-0.008	35.333	0.001
		14	0.037	0.017	36.384	0.001
		15	0.098	0.100	43.881	0.000
		16	-0.005	-0.028	43.901	0.000
		17	-0.121	-0.104	55.304	0.000
		18	-0.011	0.024	55.395	0.000
		19	0.006	0.004	55.421	0.000
		20	0.132	0.116	69.101	0.000
		21	-0.058	-0.068	71.742	0.000
		22	-0.051	-0.044	73.771	0.000
		23	-0.035	0.003	74.757	0.000
		24	-0.039	-0.063	75.962	0.000
		25	0.080	0.070	80.951	0.000
		26	-0.024	-0.053	81.392	0.000
		27	-0.090	-0.078	87.788	0.000
		28	-0.083	-0.081	93.247	0.000
		29	-0.008	-0.034	93.295	0.000
		30	0.139	0.096	108.69	0.000
		31	0.020	-0.006	109.02	0.000
		32	0.022	0.030	109.40	0.000
		33	0.012	0.009	109.51	0.000
		34	0.001	-0.014	109.51	0.000
		35	0.044	0.029	111.09	0.000
		36	0.006	0.028	111.12	0.000

Table B. 22 : The Mean equation modeling of PC4.

Dependent Variable: PC4
Method: Least Squares
Date: 07/20/10 Time: 01:05
Sample (adjusted): 1/15/2007 11/30/2009
Included observations: 751 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003518	0.016814	0.209226	0.8343
AR(3)	-0.122327	0.036033	-3.394840	0.0007
AR(5)	-0.077604	0.036069	-2.151565	0.0318
AR(10)	0.087317	0.036163	2.414574	0.0160

R-squared	0.030696	Mean dependent var	0.003572
Adjusted R-squared	0.026803	S.D. dependent var	0.519649
S.E. of regression	0.512638	Akaike info criterion	1.506818
Sum squared resid	196.3099	Schwarz criterion	1.531433
Log likelihood	-561.8103	Hannan-Quinn criter.	1.516302
F-statistic	7.885284	Durbin-Watson stat	1.915240
Prob(F-statistic)	0.000035		

Inverted AR Roots	.75	.64-.49i	.64+.49i	.25-.74i
	.25+.74i	-.23-.75i	-.23+.75i	-.62+.43i
	-.62-.43i	-.83		

Table B. 23 : Correlogram of PC4 residuals.

Correlogram of Residuals

Sample: 1/15/2007 11/30/2009
Included observations: 751
Q-statistic probabilities adjusted for 3 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	0.042	0.042	1.3075	
2	-0.047	-0.049	2.9799	
3	-0.005	-0.001	3.0017	
4	-0.043	-0.045	4.3856	0.036
5	-0.017	-0.013	4.5946	0.101
6	-0.021	-0.025	4.9433	0.176
7	-0.058	-0.058	7.4819	0.113
8	-0.069	-0.070	11.151	0.048
9	-0.037	-0.039	12.189	0.058
10	0.003	-0.005	12.195	0.094
11	-0.033	-0.045	13.048	0.110
12	0.001	-0.006	13.049	0.160
13	0.010	-0.003	13.122	0.217
14	0.027	0.018	13.666	0.252
15	0.119	0.106	24.544	0.017
16	-0.012	-0.029	24.654	0.026
17	-0.096	-0.091	31.723	0.004
18	0.002	0.004	31.726	0.007
19	-0.005	-0.009	31.742	0.011
20	0.115	0.120	42.001	0.001
21	-0.068	-0.082	45.560	0.000
22	-0.061	-0.036	48.428	0.000
23	-0.035	-0.030	49.399	0.000
24	-0.060	-0.059	52.246	0.000
25	0.080	0.073	57.209	0.000
26	-0.029	-0.047	57.846	0.000
27	-0.062	-0.054	60.854	0.000
28	-0.075	-0.091	65.270	0.000
29	0.000	-0.008	65.270	0.000
30	0.134	0.112	79.416	0.000
31	0.030	0.019	80.132	0.000
32	0.029	0.041	80.792	0.000
33	0.042	0.023	82.200	0.000
34	-0.009	-0.022	82.257	0.000
35	0.069	0.050	85.992	0.000

Table B. 24 : Correlogram of PC4 residuals squared.

Correlogram of Residuals Squared

Sample: 1/15/2007 11/30/2009
Included observations: 751
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.079	0.079	4.7451	
		2	0.031	0.025	5.4886	
		3	0.099	0.095	12.865	
		4	0.082	0.067	17.910	0.000
		5	0.017	0.001	18.117	0.000
		6	0.077	0.064	22.560	0.000
		7	0.204	0.185	54.298	0.000
		8	0.079	0.048	59.065	0.000
		9	0.018	-0.009	59.311	0.000
		10	0.182	0.147	84.507	0.000
		11	0.156	0.114	103.04	0.000
		12	0.081	0.059	108.08	0.000
		13	0.121	0.078	119.38	0.000
		14	0.147	0.076	135.89	0.000
		15	0.062	0.020	138.87	0.000
		16	0.032	-0.001	139.64	0.000
		17	0.140	0.063	154.65	0.000
		18	0.064	-0.019	157.78	0.000
		19	0.051	0.008	159.82	0.000
		20	0.158	0.090	179.22	0.000
		21	0.062	-0.039	182.21	0.000
		22	0.064	0.009	185.36	0.000
		23	0.046	-0.020	187.03	0.000
		24	0.117	0.025	197.65	0.000
		25	0.045	-0.023	199.24	0.000
		26	0.078	0.034	203.96	0.000
		27	0.176	0.092	228.28	0.000
		28	0.038	-0.033	229.38	0.000
		29	0.052	0.021	231.50	0.000
		30	0.110	0.041	241.00	0.000
		31	0.106	0.033	249.74	0.000
		32	0.054	0.014	252.06	0.000
		33	0.072	0.019	256.15	0.000
		34	0.056	-0.047	258.66	0.000
		35	0.055	0.016	261.05	0.000

Table B. 25 : Heteroskedasticity test of PC4.

Heteroskedasticity Test: ARCH

F-statistic	3.065097	Prob. F(5,745)	0.0095
Obs*R-squared	15.13752	Prob. Chi-Square(5)	0.0098

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/20/10 Time: 01:11
Sample: 1/15/2007 11/30/2009
Included observations: 751

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.198606	0.031580	6.288962	0.0000
RESID^2(-1)	0.068430	0.036637	1.867773	0.0622
RESID^2(-2)	0.016118	0.036636	0.439944	0.6601
RESID^2(-3)	0.089048	0.036397	2.446542	0.0147
RESID^2(-4)	0.066211	0.036536	1.812207	0.0704
RESID^2(-5)	0.001958	0.036517	0.053612	0.9573

R-squared	0.020156	Mean dependent var	0.261398
Adjusted R-squared	0.013580	S.D. dependent var	0.704999
S.E. of regression	0.700196	Akaike info criterion	2.133043
Sum squared resid	365.2540	Schwarz criterion	2.169965
Log likelihood	-794.9577	Hannan-Quinn criter.	2.147269
F-statistic	3.065097	Durbin-Watson stat	1.999803
Prob(F-statistic)	0.009539		

Table B. 26 : The Volatility and mean equation modeling of PC4.

Dependent Variable: PC4
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/20/10 Time: 01:11
Sample (adjusted): 1/15/2007 11/30/2009
Included observations: 751 after adjustments
Convergence achieved after 15 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002712	0.014413	0.188195	0.8507
AR(3)	-0.100790	0.034544	-2.917696	0.0035
AR(5)	-0.074449	0.041057	-1.813292	0.0698
AR(10)	0.060508	0.035467	1.706010	0.0880
		Variance Equation		
C	0.003228	0.001573	2.052404	0.0401
RESID(-1)^2	0.062098	0.016621	3.736019	0.0002
GARCH(-1)	0.925102	0.019154	48.29811	0.0000

R-squared	0.029401	Mean dependent var	0.003572
Adjusted R-squared	0.021574	S.D. dependent var	0.519649
S.E. of regression	0.514013	Akaike info criterion	1.329898
Sum squared resid	196.5720	Schwarz criterion	1.372974
Log likelihood	-492.3768	Hannan-Quinn criter.	1.346495
F-statistic	3.756222	Durbin-Watson stat	1.916466
Prob(F-statistic)	0.001085		

Inverted AR Roots	.72	.62+.48i	.62-.48i	.24-.71i
	.24+.71i	-.23-.73i	-.23+.73i	-.60+.42i
	-.60-.42i	-.80		

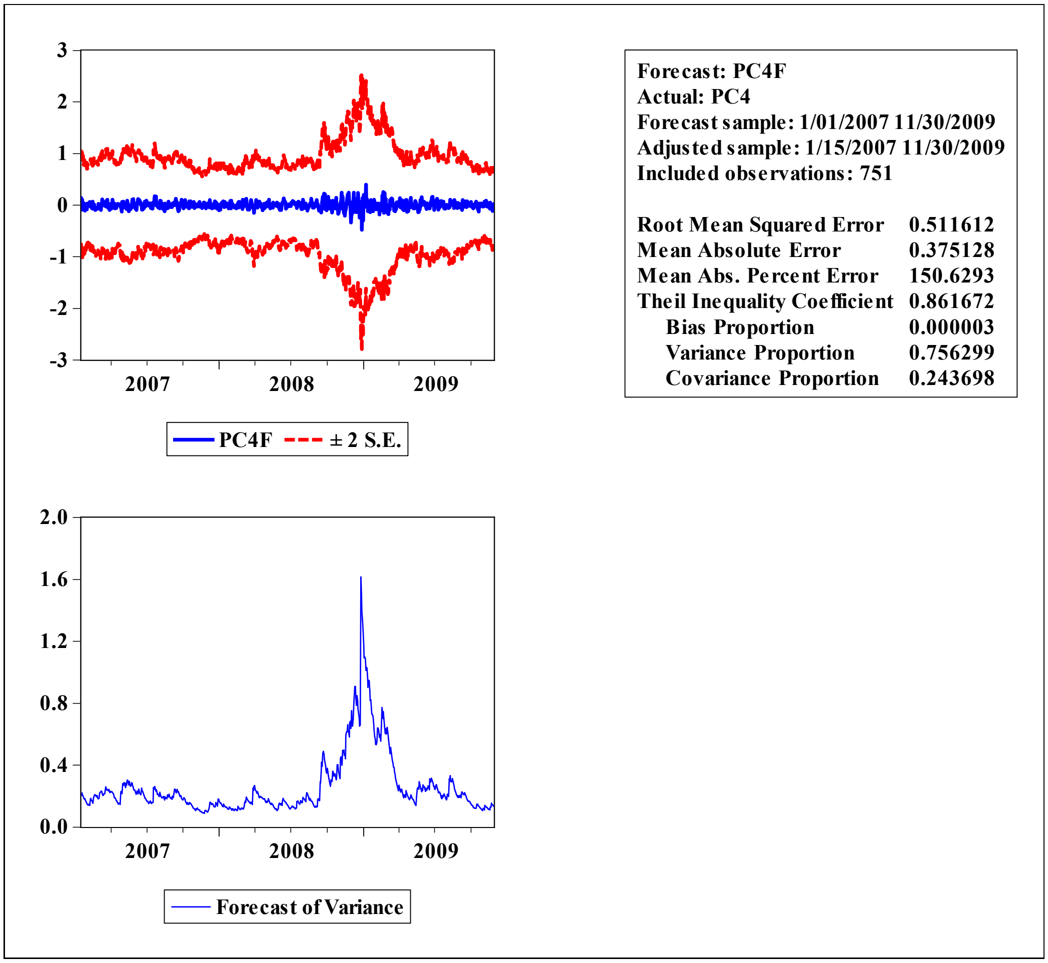


Figure B. 5 : Forecast of PC4 variance.

- **Volatility Modeling of Principal Component 5 (PC5)**

Table B. 27 : Correlogram and statistics of PC5.

Correlogram of PC5

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.350	-0.350	93.479	0.000
		2	0.026	-0.110	93.995	0.000
		3	-0.033	-0.070	94.814	0.000
		4	-0.014	-0.056	94.972	0.000
		5	-0.001	-0.033	94.973	0.000
		6	-0.008	-0.027	95.019	0.000
		7	0.023	0.009	95.437	0.000
		8	-0.042	-0.038	96.803	0.000
		9	0.001	-0.032	96.804	0.000
		10	-0.008	-0.027	96.857	0.000
		11	0.046	0.034	98.486	0.000
		12	-0.049	-0.027	100.34	0.000
		13	0.031	0.006	101.10	0.000
		14	-0.016	-0.006	101.29	0.000
		15	0.033	0.032	102.12	0.000
		16	-0.026	-0.005	102.66	0.000
		17	0.028	0.022	103.27	0.000
		18	-0.095	-0.091	110.30	0.000
		19	0.014	-0.056	110.46	0.000
		20	0.030	0.004	111.16	0.000
		21	-0.071	-0.076	115.12	0.000
		22	-0.006	-0.080	115.15	0.000
		23	0.074	0.046	119.44	0.000
		24	0.000	0.039	119.44	0.000
		25	0.027	0.055	120.03	0.000
		26	-0.004	0.026	120.04	0.000
		27	-0.030	-0.019	120.74	0.000
		28	0.027	0.017	121.34	0.000
		29	-0.062	-0.049	124.42	0.000
		30	0.027	-0.031	125.01	0.000
		31	-0.019	-0.026	125.30	0.000
		32	-0.019	-0.035	125.58	0.000
		33	0.010	-0.011	125.65	0.000
		34	0.002	-0.008	125.66	0.000
		35	-0.012	-0.021	125.77	0.000
		36	0.016	-0.004	125.98	0.000

Table B. 28 : The Mean equation modeling of PC5.

Dependent Variable: PC5
Method: Least Squares
Date: 07/20/10 Time: 01:19
Sample (adjusted): 1/02/2007 11/30/2009
Included observations: 760 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.34E-06	0.008712	-0.000498	0.9996
AR(1)	-0.349794	0.034027	-10.27982	0.0000

R-squared	0.122355	Mean dependent var	4.97E-06
Adjusted R-squared	0.121197	S.D. dependent var	0.345822
S.E. of regression	0.324190	Akaike info criterion	0.587651
Sum squared resid	79.66494	Schwarz criterion	0.599844
Log likelihood	-221.3075	Hannan-Quinn criter.	0.592347
F-statistic	105.6748	Durbin-Watson stat	2.076159
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.35

Table B. 29 : Correlogram and statistics of PC5 residuals.

Correlogram of Residuals

Sample: 1/02/2007 11/30/2009
Included observations: 760
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.038	-0.038	1.1245	
		2	-0.119	-0.121	11.980	0.001
		3	-0.037	-0.048	13.039	0.001
		4	-0.032	-0.051	13.811	0.003
		5	-0.010	-0.025	13.885	0.008
		6	-0.001	-0.015	13.886	0.016
		7	0.010	0.001	13.961	0.030
		8	-0.044	-0.050	15.455	0.031
		9	-0.019	-0.025	15.721	0.047
		10	0.008	-0.007	15.772	0.072
		11	0.036	0.027	16.769	0.080
		12	-0.032	-0.035	17.547	0.093
		13	0.014	0.016	17.704	0.125
		14	0.005	0.000	17.727	0.168
		15	0.025	0.030	18.221	0.197
		16	-0.009	-0.008	18.286	0.248
		17	-0.012	-0.007	18.404	0.301
		18	-0.104	-0.108	26.905	0.059
		19	-0.008	-0.016	26.950	0.080
		20	0.015	-0.016	27.138	0.101
		21	-0.081	-0.098	32.316	0.040
		22	-0.006	-0.030	32.346	0.054
		23	0.092	0.070	39.036	0.014
		24	0.041	0.033	40.339	0.014
		25	0.034	0.052	41.231	0.016
		26	-0.006	0.001	41.256	0.022
		27	-0.029	-0.013	41.906	0.025
		28	-0.002	0.005	41.908	0.034
		29	-0.058	-0.061	44.562	0.024
		30	0.002	-0.019	44.566	0.032
		31	-0.021	-0.031	44.916	0.039
		32	-0.028	-0.028	45.519	0.045
		33	0.006	-0.004	45.548	0.057
		34	0.002	-0.014	45.551	0.072
		35	-0.008	-0.017	45.603	0.088

Table B. 30 : Correlogram and statistics of PC5 residuals squared.

Correlogram of Residuals Squared

Sample: 1/02/2007 11/30/2009
Included observations: 760
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.452	0.452	155.60	
		2	0.079	-0.157	160.32	0.000
		3	-0.020	0.013	160.64	0.000
		4	-0.021	-0.005	160.99	0.000
		5	-0.027	-0.024	161.57	0.000
		6	-0.021	0.000	161.91	0.000
		7	-0.012	-0.005	162.03	0.000
		8	-0.020	-0.019	162.33	0.000
		9	-0.034	-0.023	163.24	0.000
		10	-0.025	-0.000	163.74	0.000
		11	-0.008	0.001	163.79	0.000
		12	-0.018	-0.024	164.03	0.000
		13	-0.012	0.006	164.14	0.000
		14	-0.001	0.000	164.14	0.000
		15	0.021	0.023	164.48	0.000
		16	-0.004	-0.032	164.49	0.000
		17	-0.007	0.010	164.53	0.000
		18	-0.006	-0.008	164.56	0.000
		19	-0.008	-0.006	164.61	0.000
		20	0.006	0.017	164.64	0.000
		21	0.078	0.085	169.40	0.000
		22	0.135	0.076	183.69	0.000
		23	0.104	0.012	192.20	0.000
		24	0.017	-0.034	192.43	0.000
		25	-0.019	0.002	192.71	0.000
		26	-0.033	-0.023	193.57	0.000
		27	-0.033	-0.007	194.45	0.000
		28	-0.023	-0.004	194.87	0.000
		29	0.009	0.027	194.94	0.000
		30	0.023	0.011	195.37	0.000
		31	0.000	-0.013	195.37	0.000
		32	-0.019	-0.011	195.66	0.000
		33	-0.028	-0.017	196.30	0.000
		34	-0.018	0.004	196.55	0.000

Table B. 31 : Heteroskedasticity test of PC5.

Heteroskedasticity Test: ARCH

F-statistic	43.36649	Prob. F(5,750)	0.0000
Obs*R-squared	169.5489	Prob. Chi-Square(5)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/20/10 Time: 01:22
Sample (adjusted): 1/08/2007 11/30/2009
Included observations: 756 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.067781	0.013827	4.902065	0.0000
RESID^2(-1)	0.524661	0.036504	14.37266	0.0000
RESID^2(-2)	-0.164511	0.041225	-3.990609	0.0001
RESID^2(-3)	0.011138	0.041658	0.267360	0.7893
RESID^2(-4)	0.007946	0.041225	0.192748	0.8472
RESID^2(-5)	-0.023972	0.036504	-0.656692	0.5116

R-squared	0.224271	Mean dependent var	0.105127
Adjusted R-squared	0.219099	S.D. dependent var	0.390922
S.E. of regression	0.345453	Akaike info criterion	0.719983
Sum squared resid	89.50315	Schwarz criterion	0.756713
Log likelihood	-266.1534	Hannan-Quinn criter.	0.734130
F-statistic	43.36649	Durbin-Watson stat	1.999993
Prob(F-statistic)	0.000000		

Table B. 32 : The Volatility and mean equation modeling of PC5.

Dependent Variable: PC5
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/20/10 Time: 01:23
Sample (adjusted): 1/02/2007 11/30/2009
Included observations: 760 after adjustments
Convergence achieved after 52 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(6)*RESID(-1)
/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)*LOG(GARCH(
-2))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.008926	0.004831	-1.847578	0.0647
AR(1)	-0.226365	0.047092	-4.806843	0.0000
		Variance Equation		
C(3)	-0.444674	0.066986	-6.638329	0.0000
C(4)	0.782907	0.070804	11.05742	0.0000
C(5)	-0.714215	0.063163	-11.30755	0.0000
C(6)	-0.105493	0.018665	-5.652082	0.0000
C(7)	1.506569	0.048909	30.80338	0.0000
C(8)	-0.659481	0.039635	-16.63901	0.0000

R-squared	0.106118	Mean dependent var	4.97E-06
Adjusted R-squared	0.097797	S.D. dependent var	0.345822
S.E. of regression	0.328477	Akaike info criterion	0.229515
Sum squared resid	81.13882	Schwarz criterion	0.278287
Log likelihood	-79.21560	Hannan-Quinn criter.	0.248296
F-statistic	12.75342	Durbin-Watson stat	2.300284
Prob(F-statistic)	0.000000		
Inverted AR Roots	-.23		

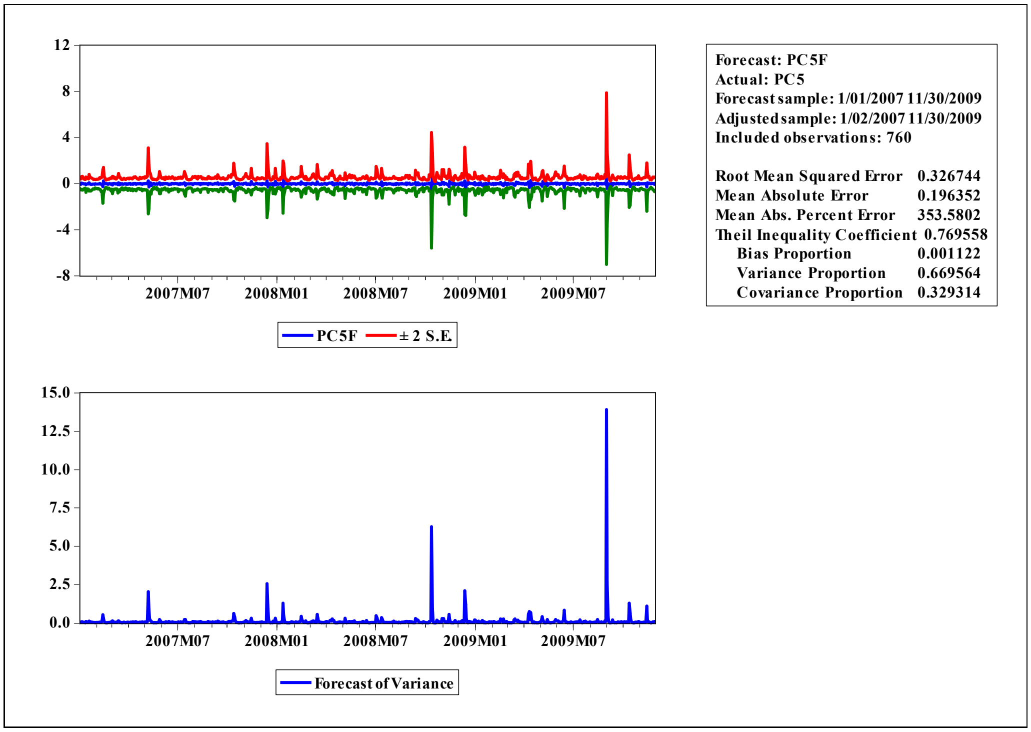


Figure B. 6 : Forecast of PC5 variance.

- **Volatility Modeling of Principal Component 6 (PC6)**

Table B. 33 : Correlogram and statistics of PC6.

Correlogram of PC6

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.033	-0.033	0.8531	0.356
		2	-0.016	-0.018	1.0584	0.589
		3	-0.040	-0.041	2.2801	0.516
		4	-0.103	-0.106	10.354	0.035
		5	0.007	-0.002	10.391	0.065
		6	-0.054	-0.061	12.647	0.049
		7	-0.029	-0.043	13.277	0.066
		8	-0.027	-0.044	13.851	0.086
		9	-0.050	-0.061	15.765	0.072
		10	0.080	0.059	20.719	0.023
		11	-0.009	-0.018	20.783	0.036
		12	0.035	0.022	21.754	0.040
		13	-0.081	-0.091	26.895	0.013
		14	0.011	0.014	26.989	0.019
		15	0.026	0.014	27.515	0.025
		16	0.039	0.044	28.698	0.026
		17	0.017	0.004	28.921	0.035
		18	-0.049	-0.039	30.786	0.030
		19	0.029	0.036	31.449	0.036
		20	-0.034	-0.034	32.330	0.040
		21	-0.039	-0.039	33.506	0.041
		22	0.002	-0.017	33.510	0.055
		23	-0.095	-0.078	40.548	0.013
		24	-0.071	-0.097	44.509	0.007
		25	0.042	0.029	45.878	0.007
		26	0.038	0.010	47.030	0.007
		27	-0.024	-0.060	47.498	0.009
		28	0.074	0.064	51.805	0.004
		29	-0.004	-0.009	51.818	0.006
		30	0.061	0.059	54.801	0.004
		31	-0.030	-0.045	55.529	0.004
		32	-0.072	-0.064	59.662	0.002
		33	0.044	0.044	61.225	0.002
		34	-0.012	0.014	61.332	0.003
		35	-0.008	-0.017	61.384	0.004
		36	-0.063	-0.087	64.558	0.002

Table B. 34 : The Mean equation modeling of PC6.

Dependent Variable: PC6
Method: Least Squares
Date: 07/20/10 Time: 09:24
Sample (adjusted): 1/05/2007 11/30/2009
Included observations: 757 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000916	0.010892	-0.084129	0.9330
AR(4)	-0.102727	0.036169	-2.840233	0.0046

R-squared	0.010572	Mean dependent var	-0.000973
Adjusted R-squared	0.009261	S.D. dependent var	0.332001
S.E. of regression	0.330460	Akaike info criterion	0.625976
Sum squared resid	82.44883	Schwarz criterion	0.638207
Log likelihood	-234.9318	Hannan-Quinn criter.	0.630686
F-statistic	8.066926	Durbin-Watson stat	2.076573
Prob(F-statistic)	0.004629		

Inverted AR Roots	.40+.40i	.40+.40i	-.40+.40i	-.40+.40i

Table B. 35 : Correlogram and statistics of PC6 residuals.

Correlogram of Residuals

Sample: 1/05/2007 11/30/2009
Included observations: 757
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.041	-0.041	1.2467	
		2	-0.027	-0.029	1.8166	0.178
		3	-0.050	-0.052	3.7020	0.157
		4	-0.005	-0.010	3.7183	0.294
		5	-0.001	-0.004	3.7185	0.445
		6	-0.047	-0.051	5.4393	0.365
		7	-0.030	-0.036	6.1329	0.408
		8	-0.035	-0.042	7.0987	0.419
		9	-0.056	-0.068	9.5359	0.299
		10	0.080	0.068	14.402	0.109
		11	-0.009	-0.011	14.458	0.153
		12	0.042	0.036	15.798	0.149
		13	-0.087	-0.083	21.657	0.042
		14	0.017	0.007	21.889	0.057
		15	0.028	0.020	22.497	0.069
		16	0.040	0.038	23.732	0.070
		17	0.004	0.008	23.744	0.095
		18	-0.051	-0.042	25.780	0.079
		19	0.021	0.024	26.117	0.097
		20	-0.038	-0.047	27.232	0.099
		21	-0.034	-0.038	28.145	0.106
		22	0.001	-0.013	28.146	0.136
		23	-0.098	-0.089	35.681	0.033
		24	-0.069	-0.089	39.439	0.018
		25	0.033	0.025	40.299	0.020
		26	0.048	0.017	42.116	0.017
		27	-0.043	-0.061	43.549	0.017
		28	0.064	0.068	46.775	0.010
		29	0.003	-0.010	46.782	0.014
		30	0.067	0.061	50.353	0.008
		31	-0.032	-0.039	51.185	0.009
		32	-0.072	-0.079	55.302	0.005
		33	0.041	0.042	56.619	0.005
		34	-0.004	0.008	56.630	0.006
		35	-0.016	-0.015	56.831	0.008

Table B. 36 : Correlogram of PC6 residuals squared.

Correlogram of Residuals Squared

Sample: 1/05/2007 11/30/2009
Included observations: 757
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.163	0.163	20.084	
		2	0.112	0.088	29.585	0.000
		3	0.088	0.059	35.500	0.000
		4	0.250	0.228	83.242	0.000
		5	0.166	0.097	104.42	0.000
		6	0.235	0.178	146.62	0.000
		7	0.137	0.059	160.90	0.000
		8	0.194	0.105	189.68	0.000
		9	0.132	0.036	203.03	0.000
		10	0.154	0.033	221.28	0.000
		11	0.228	0.143	261.38	0.000
		12	0.118	-0.030	272.12	0.000
		13	0.187	0.102	299.11	0.000
		14	0.083	-0.051	304.44	0.000
		15	0.167	0.047	325.92	0.000
		16	0.169	0.066	348.07	0.000
		17	0.252	0.116	397.51	0.000
		18	0.073	-0.032	401.67	0.000
		19	0.143	0.016	417.58	0.000
		20	0.100	-0.001	425.31	0.000
		21	0.243	0.099	471.35	0.000
		22	0.030	-0.120	472.04	0.000
		23	0.082	-0.042	477.34	0.000
		24	0.202	0.121	509.27	0.000
		25	0.147	-0.016	526.29	0.000
		26	0.076	-0.014	530.85	0.000
		27	0.077	-0.041	535.48	0.000
		28	0.081	-0.045	540.60	0.000
		29	0.082	-0.021	545.88	0.000
		30	0.144	0.034	562.26	0.000
		31	0.125	0.063	574.72	0.000
		32	0.055	-0.101	577.10	0.000
		33	0.068	0.039	580.82	0.000
		34	0.107	-0.004	589.98	0.000

Table B. 37 : Heteroskedasticity test of PC6.

Heteroskedasticity Test: ARCH

F-statistic	15.81483	Prob. F(5,750)	0.0000
Obs*R-squared	72.10458	Prob. Chi-Square(5)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/20/10 Time: 09:27
Sample (adjusted): 1/08/2007 11/30/2009
Included observations: 756 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.054180	0.010806	5.013739	0.0000
RESID^2(-1)	0.107795	0.036332	2.966973	0.0031
RESID^2(-2)	0.058111	0.035674	1.628938	0.1037
RESID^2(-3)	0.020295	0.035724	0.568105	0.5701
RESID^2(-4)	0.214191	0.035651	6.007906	0.0000
RESID^2(-5)	0.096825	0.036280	2.668851	0.0078

R-squared	0.095376	Mean dependent var	0.108688
Adjusted R-squared	0.089346	S.D. dependent var	0.241990
S.E. of regression	0.230927	Akaike info criterion	-0.085524
Sum squared resid	39.99551	Schwarz criterion	-0.048794
Log likelihood	38.32814	Hannan-Quinn criter.	-0.071376
F-statistic	15.81483	Durbin-Watson stat	2.033603
Prob(F-statistic)	0.000000		

Table B. 38 : The Volatility and mean equation modeling of PC6.

Dependent Variable: PC6
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/20/10 Time: 09:26
Sample (adjusted): 1/05/2007 11/30/2009
Included observations: 757 after adjustments
Convergence achieved after 11 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003057	0.009219	0.331600	0.7402
AR(4)	-0.087287	0.035949	-2.428103	0.0152
		Variance Equation		
C	0.001909	0.000601	3.179285	0.0015
RESID(-1)^2	0.065068	0.013565	4.796885	0.0000
GARCH(-1)	0.914828	0.016665	54.89410	0.0000

R-squared	0.010163	Mean dependent var	-0.000973
Adjusted R-squared	0.004898	S.D. dependent var	0.332001
S.E. of regression	0.331187	Akaike info criterion	0.438367
Sum squared resid	82.48292	Schwarz criterion	0.468944
Log likelihood	-160.9220	Hannan-Quinn criter.	0.450144
F-statistic	1.930201	Durbin-Watson stat	2.074958
Prob(F-statistic)	0.103550		

Inverted AR Roots	.38-.38i	.38-.38i	-.38+.38i	-.38+.38i

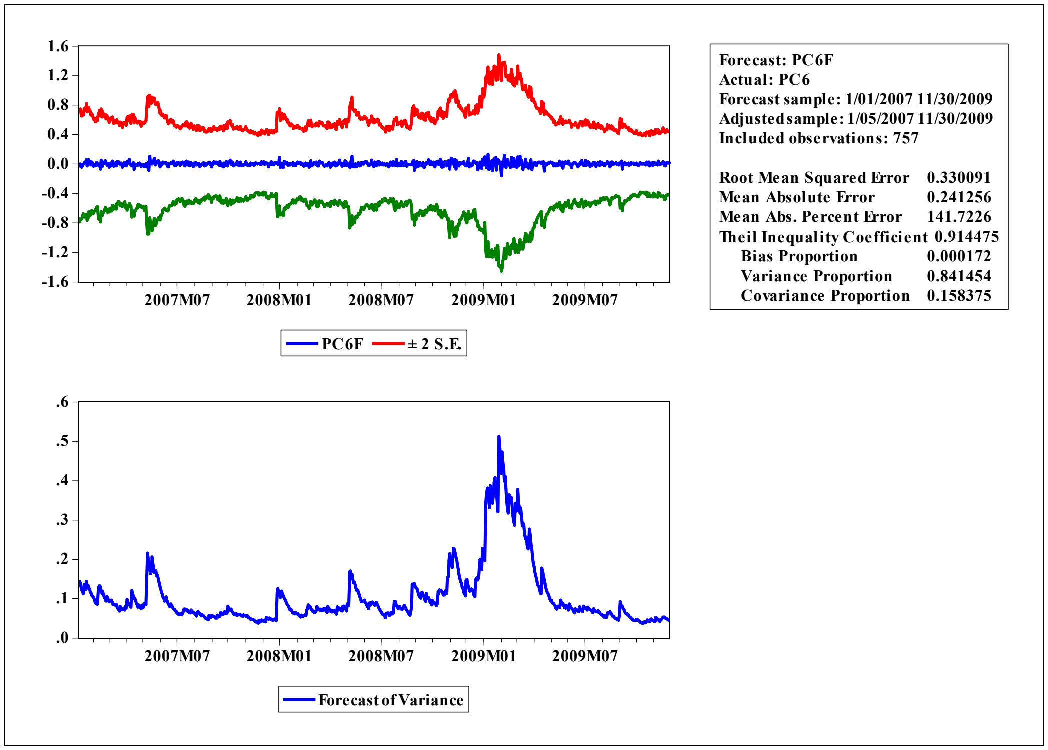


Figure B. 7 : Forecast of PC6 variance.

- **Volatility Modeling of Principal Component 7 (PC7)**

Table B. 39 : Correlogram and statistics of PC7.

Correlogram of PC7

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.058	0.058	2.6041	0.107
		2	-0.030	-0.034	3.3083	0.191
		3	-0.064	-0.060	6.4276	0.093
		4	-0.021	-0.015	6.7735	0.148
		5	-0.028	-0.029	7.3565	0.195
		6	-0.001	-0.003	7.3575	0.289
		7	-0.023	-0.027	7.7668	0.354
		8	0.011	0.010	7.8650	0.447
		9	-0.080	-0.085	12.768	0.173
		10	0.051	0.058	14.762	0.141
		11	-0.010	-0.022	14.844	0.190
		12	0.000	-0.005	14.844	0.250
		13	-0.055	-0.053	17.225	0.189
		14	0.042	0.045	18.613	0.180
		15	0.027	0.021	19.190	0.205
		16	-0.003	-0.014	19.195	0.259
		17	-0.045	-0.036	20.793	0.236
		18	0.034	0.032	21.698	0.246
		19	-0.035	-0.031	22.647	0.253
		20	-0.081	-0.089	27.764	0.115
		21	-0.060	-0.046	30.578	0.081
		22	-0.024	-0.038	31.024	0.096
		23	-0.012	-0.011	31.144	0.119
		24	0.059	0.043	33.886	0.087
		25	-0.050	-0.071	35.862	0.074
		26	-0.004	-0.010	35.872	0.094
		27	-0.034	-0.025	36.808	0.099
		28	-0.041	-0.055	38.115	0.096
		29	-0.045	-0.060	39.722	0.089
		30	0.028	0.019	40.342	0.098
		31	-0.023	-0.032	40.773	0.113
		32	0.029	0.015	41.442	0.123
		33	-0.055	-0.067	43.875	0.098
		34	0.019	0.006	44.167	0.114
		35	0.041	0.050	45.493	0.110
		36	0.039	0.018	46.711	0.109

Table B. 40 : The Mean equation modeling of PC7.

Dependent Variable: PC7
Method: Least Squares
Date: 07/20/10 Time: 09:42
Sample: 1/01/2007 11/30/2009
Included observations: 761

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.97E-17	0.006757	5.88E-15	1.0000

R-squared	0.000000	Mean dependent var	3.61E-17
Adjusted R-squared	0.000000	S.D. dependent var	0.186401
S.E. of regression	0.186401	Akaike info criterion	-0.520521
Sum squared resid	26.40643	Schwarz criterion	-0.514430
Log likelihood	199.0581	Hannan-Quinn criter.	-0.518176
Durbin-Watson stat	1.882864		

Table B. 41 : Correlogram and statistics of PC7 residuals.

Correlogram of Residuals

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.058	0.058	2.6041	0.107
		2	-0.030	-0.034	3.3083	0.191
		3	-0.064	-0.060	6.4276	0.093
		4	-0.021	-0.015	6.7735	0.148
		5	-0.028	-0.029	7.3565	0.195
		6	-0.001	-0.003	7.3575	0.289
		7	-0.023	-0.027	7.7668	0.354
		8	0.011	0.010	7.8650	0.447
		9	-0.080	-0.085	12.768	0.173
		10	0.051	0.058	14.762	0.141
		11	-0.010	-0.022	14.844	0.190
		12	0.000	-0.005	14.844	0.250
		13	-0.055	-0.053	17.225	0.189
		14	0.042	0.045	18.613	0.180
		15	0.027	0.021	19.190	0.205
		16	-0.003	-0.014	19.195	0.259
		17	-0.045	-0.036	20.793	0.236
		18	0.034	0.032	21.698	0.246
		19	-0.035	-0.031	22.647	0.253
		20	-0.081	-0.089	27.764	0.115
		21	-0.060	-0.046	30.578	0.081
		22	-0.024	-0.038	31.024	0.096
		23	-0.012	-0.011	31.144	0.119
		24	0.059	0.043	33.886	0.087
		25	-0.050	-0.071	35.862	0.074
		26	-0.004	-0.010	35.872	0.094
		27	-0.034	-0.025	36.808	0.099
		28	-0.041	-0.055	38.115	0.096
		29	-0.045	-0.060	39.722	0.089
		30	0.028	0.019	40.342	0.098
		31	-0.023	-0.032	40.773	0.113
		32	0.029	0.015	41.442	0.123
		33	-0.055	-0.067	43.875	0.098
		34	0.019	0.006	44.167	0.114
		35	0.041	0.050	45.493	0.110
		36	0.039	0.018	46.711	0.109

Table B. 42 : Correlogram of PC7 residuals squared.

Correlogram of Residuals Squared

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.073	0.073	4.0882	0.043
		2	0.078	0.073	8.7396	0.013
		3	0.090	0.080	14.960	0.002
		4	0.057	0.041	17.423	0.002
		5	0.029	0.011	18.060	0.003
		6	0.018	0.002	18.312	0.005
		7	0.069	0.059	22.016	0.003
		8	0.038	0.025	23.154	0.003
		9	-0.031	-0.048	23.910	0.004
		10	0.005	-0.006	23.932	0.008
		11	0.000	-0.006	23.932	0.013
		12	-0.001	0.001	23.933	0.021
		13	-0.018	-0.016	24.186	0.029
		14	0.005	0.005	24.208	0.043
		15	-0.024	-0.026	24.657	0.055
		16	0.023	0.033	25.082	0.068
		17	-0.002	0.001	25.087	0.093
		18	0.047	0.047	26.789	0.083
		19	0.019	0.012	27.067	0.103
		20	0.032	0.026	27.880	0.112
		21	0.022	0.010	28.255	0.133
		22	0.054	0.045	30.531	0.106
		23	0.005	-0.011	30.555	0.134
		24	0.028	0.012	31.153	0.149
		25	-0.000	-0.016	31.153	0.184
		26	-0.029	-0.042	31.822	0.199
		27	0.082	0.084	37.123	0.093
		28	0.035	0.026	38.083	0.097
		29	0.018	0.007	38.351	0.115
		30	0.036	0.019	39.381	0.117
		31	-0.008	-0.019	39.434	0.142
		32	0.021	0.012	39.770	0.163
		33	0.022	0.028	40.172	0.182
		34	0.062	0.049	43.291	0.132
		35	0.017	-0.003	43.536	0.153

Table B. 43 : Heteroskedasticity test of PC7.

Heteroskedasticity Test: ARCH

F-statistic	2.869325	Prob. F(5,750)	0.0142
Obs*R-squared	14.18996	Prob. Chi-Square(5)	0.0144

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/20/10 Time: 09:44
Sample (adjusted): 1/08/2007 11/30/2009
Included observations: 756 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.026081	0.003223	8.093212	0.0000
RESID^2(-1)	0.058161	0.036507	1.593143	0.1115
RESID^2(-2)	0.064302	0.036542	1.759689	0.0789
RESID^2(-3)	0.077148	0.036514	2.112794	0.0349
RESID^2(-4)	0.039724	0.036554	1.086698	0.2775
RESID^2(-5)	0.010997	0.036518	0.301145	0.7634

R-squared	0.018770	Mean dependent var	0.034805
Adjusted R-squared	0.012228	S.D. dependent var	0.057254
S.E. of regression	0.056902	Akaike info criterion	-2.887054
Sum squared resid	2.428411	Schwarz criterion	-2.850324
Log likelihood	1097.307	Hannan-Quinn criter.	-2.872906
F-statistic	2.869325	Durbin-Watson stat	2.000343
Prob(F-statistic)	0.014158		

Table B. 44 : The Mean equation modeling of PC7.

Dependent Variable: PC7
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/20/10 Time: 09:45
Sample: 1/01/2007 11/30/2009
Included observations: 761
Convergence achieved after 9 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000208	0.006569	-0.031618	0.9748
		Variance Equation		
C	0.006069	0.002933	2.069040	0.0385
RESID(-1)^2	0.082686	0.032007	2.583389	0.0098
GARCH(-1)	0.742856	0.106063	7.003927	0.0000

R-squared	-0.000001	Mean dependent var	3.61E-17
Adjusted R-squared	-0.003964	S.D. dependent var	0.186401
S.E. of regression	0.186770	Akaike info criterion	-0.534785
Sum squared resid	26.40646	Schwarz criterion	-0.510424
Log likelihood	207.4856	Hannan-Quinn criter.	-0.525404
Durbin-Watson stat	1.882862		

Table B. 45 : Correlogram of PC7 standardized residuals.

Correlogram of Standardized Residuals

Sample: 1/01/2007 11/30/2009
Included observations: 761

	AC	PAC	Q-Stat	Prob
1	0.053	0.053	2.1321	0.144
2	-0.032	-0.035	2.9333	0.231
3	-0.053	-0.049	5.0690	0.167
4	-0.023	-0.019	5.4827	0.241
5	-0.010	-0.011	5.5538	0.352
6	-0.002	-0.005	5.5580	0.474
7	-0.018	-0.020	5.8041	0.563
8	0.015	0.016	5.9833	0.649
9	-0.072	-0.076	9.9723	0.353
10	0.049	0.057	11.863	0.294
11	-0.009	-0.020	11.931	0.369
12	-0.008	-0.010	11.983	0.447
13	-0.048	-0.047	13.800	0.388
14	0.038	0.043	14.940	0.382
15	0.019	0.010	15.215	0.436
16	-0.010	-0.017	15.294	0.503
17	-0.042	-0.034	16.703	0.475
18	0.044	0.043	18.246	0.440
19	-0.025	-0.026	18.736	0.474
20	-0.075	-0.081	23.157	0.281
21	-0.063	-0.052	26.284	0.196
22	-0.013	-0.021	26.418	0.234
23	-0.006	-0.007	26.446	0.280
24	0.049	0.035	28.305	0.247
25	-0.052	-0.066	30.411	0.209
26	-0.008	-0.010	30.457	0.249
27	-0.040	-0.029	31.693	0.244
28	-0.052	-0.064	33.850	0.206
29	-0.054	-0.067	36.145	0.169
30	0.040	0.035	37.401	0.166
31	-0.015	-0.023	37.586	0.193
32	0.024	0.008	38.051	0.213
33	-0.058	-0.068	40.706	0.167
34	0.018	0.010	40.961	0.192
35	0.045	0.053	42.546	0.178

Table B. 46 : Correlogram and statistics of PC7 standardized residuals squared.

Correlogram of Standardized Residuals Squared

Sample: 1/01/2007 11/30/2009
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.012	-0.012	0.1189	0.730
		2	-0.016	-0.016	0.3172	0.853
		3	0.025	0.025	0.8119	0.847
		4	0.005	0.005	0.8314	0.934
		5	-0.004	-0.003	0.8428	0.974
		6	-0.022	-0.023	1.2307	0.975
		7	0.065	0.064	4.4821	0.723
		8	-0.006	-0.005	4.5110	0.808
		9	-0.041	-0.038	5.8137	0.758
		10	-0.013	-0.017	5.9429	0.820
		11	-0.020	-0.022	6.2381	0.857
		12	-0.009	-0.008	6.3050	0.900
		13	-0.016	-0.013	6.5125	0.926
		14	0.010	0.006	6.5889	0.949
		15	-0.028	-0.029	7.2197	0.951
		16	0.015	0.020	7.3979	0.965
		17	-0.011	-0.012	7.4973	0.976
		18	0.042	0.044	8.8716	0.963
		19	0.011	0.010	8.9679	0.974
		20	0.011	0.013	9.0644	0.982
		21	0.006	0.001	9.0936	0.988
		22	0.048	0.051	10.902	0.976
		23	-0.015	-0.018	11.085	0.982
		24	0.019	0.021	11.382	0.986
		25	-0.016	-0.023	11.574	0.990
		26	-0.033	-0.035	12.439	0.988
		27	0.058	0.059	15.070	0.968
		28	0.029	0.034	15.753	0.969
		29	0.009	0.011	15.824	0.977
		30	0.026	0.029	16.356	0.980
		31	-0.023	-0.021	16.781	0.982
		32	0.002	0.002	16.783	0.988
		33	0.027	0.040	17.376	0.988
		34	0.060	0.054	20.241	0.970
		35	0.005	0.005	20.260	0.978

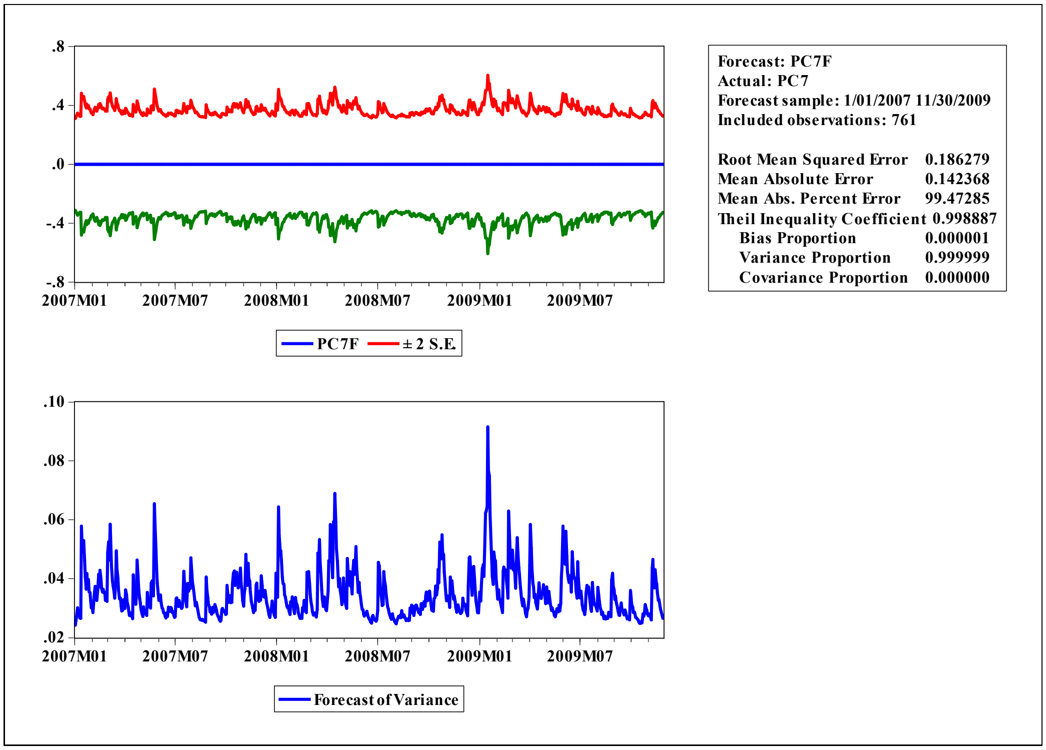
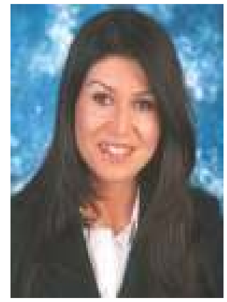


Figure B. 8 : Forecast of PC7 variance.



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